JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Intracranial Tumor Segmentation: An Advanced Software Tool for Brain Tumor Detection and Segmentation

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***Abstract* :** We propose a novel multimodal medical image fusion method for brain tumors, integrating MRI and CT scans. Utilizing VGG-19 mesh-based fusion, our method generates LL, LH, LV, and LD bands for four image groups, eliminating redundant data. The approach demonstrates effectiveness in identifying brain lesions by employing deep convolutional neural networks like VGG-19. The method involves merging discrete wavelet-transformed images and reconstructing them using an adaptive transform. Evaluation is performed on collected brain MRI and CT images, showcasing the method's potential for enhanced diagnostic information.

***Index Terms* - Computed Tomography (CT), Multimodal medical image fusion, Brain tumor detection, VGG-19 algorithm, Magnetic Resonance Imaging(MRI).**

I. INTRODUCTION

Image fusion is a technique that combines the spatial dimensions of multiple images to create a single image. It is widely used in medical imaging to enhance the quality of analysis and diagnosis by preserving the spatial characteristics of the images. The primary goal is to increase precision and speed while maintaining the original image quality. This technique is useful in image enhancement, processing, and monitoring, resulting in accurate illness categorization and diagnosis. Traditional medical image fusion techniques, such as medical image registration, create a single output image from multiple input pictures, aligning them from multiple sources. This method is used in disease classification, weather forecasting, and military tasks. Deep learning is particularly effective in image fusion, segmentation, and facial expression detection.

Advances in medical equipment and methods like computed and positron tomography and magnetic resonance imaging have improved disease diagnosis accuracy and speed. MRI provides in-depth information on physiology, tissue makeup, and hemodynamics, making image fusion crucial for accurate results. This method combines data from various images into a unique fused image, making analysis simpler, faster, and more precise. Image fusion also improves spatial sharpness and reduces storage area for individual images. MRI and CT scans offer better resolution and anatomical structure, making them valuable tools for medical diagnosis.

Brain tumors affect 15 million people globally annually, and early detection is crucial for preventing complications and saving lives. Deep learning algorithms are used to diagnose stroke using brain images from computed tomography, MRI, and CT scans. A multimodal medical picture is used to identify brain tumors, and a reliable deep learning model is developed. The proposed method integrates different medical imaging modalities, including CT and MRI images, to detect brain cancer. Generative adversarial networks combine CT and MRI images to enhance a patient's prognosis.

II. LITERATURE SEARCH APPROACH

Suresha D. et al. [16] created a system that uses a combination of SVM and K-Means to determine if the brain contains a tumor or not from an MR image. The spots are discovered after the input image is transformed to grayscale using binary thresholding. K-means is utilized to assess the features acquired from the image after grouping the spots, and Support Vector Machine (SVM) is effectively implemented. The method detects irregularities in the brain revealed by the MR picture. The technology has a small learning curve, aids in tumor diagnosis more quickly, and produces reliable findings.

Leena Chandrashekar et al. [17] established a framework for combining CT and MR images to produce a single, visually better image, in order to aid in the early diagnosis of glioblastoma. The framework's first phases include CT and MR image preprocessing, image registration, fusing multiple pictures into a one picture, augmentation, and segmentation Regarding the performance parameters, it displays improved results.

Ming li et al. [18] proposed multi-CNNs, a multimodal data fusion and CNN combination technique for brain cancer diagnosis that are used to address the issue of low precision in old brain tumor detection. By expanding 2D-CNNs to multimodal 3DCNNs, it is possible to produce brain lesions with diverse modal features of three- dimensional space.

Deep learning is used to develop brain tumor detection and classification models using magnetic resonance imaging (MRI) data in order to identify brain tumors quickly and easily. The model has been developed and put into use, together with a dataset of 10,000 images for the purpose of detecting brain tumors using deep learning approaches that utilize neural networks. They used Reset, Inception, Mobile Net, and VGG16 for testing, and the accuracy reached was 98.28 percent, while ResNet50's accuracy was 98.14%, InceptionV3's accuracy was 99.88%, Mobile Net’s accuracy was 88.98%, and VGG16's accuracy was 99.86%[19].

In addition, (DLA) a deep learning architecture was created to aid in automatic identification of brain tumors using 2-dimensional MR imaging segments. To detect brain cancers, the author recommends combining pre- trained deep learning architectures such as ResNet50, VGG16, Alex Net, and ResNet101 and VGG19 with the SoftMax classifier, which is based on deep features. In addition, SVM-linear, SVM-RBF, decision tree (DT) and K Nearest Neighbor (KNN) and are used in the architecture of pre-trained deep learning along with deep features-based classification and a VGG19 network with crafted and serially fusing deep features to improve brain tumor detection accuracy. Separate MRI slices with the T1C, T2 and Flair modalities were utilized for the research study. The study's findings revealed that the VGG19 with SVM-RBF improved classification accuracy with T1C greater than 97%, T2 achieving greater than 98% and Flair with the highest that is greater than 99% [20].

Using an Artificial Neural Network (ANN) and image fusion, the author presented a method for automatically segmenting and detecting brain tumors. This method suggests an efficient wavelet-based fusion algorithm for tumor detection that makes use of the redundant and complementary data from CT and MRI images. This technique efficiently combines the data from the MRI and CT images, resulting in a fused image that improves the accuracy of brain tumor detection. Thresholding is used to perform segmentation of the fused image. Brain tumors are automatically detected from segmented brain images using feed-forward neural networks [21].

III. FEATURES

Incorporating the insights from the provided paragraphs, the advanced software tool for brain tumor detection and segmentation boasts a novel multimodal medical image fusion method leveraging MRI and CT scans. Employing VGG-19 mesh-based fusion, it generates LL, LH, LV, and LD bands for four image groups, effectively eliminating redundant data. Deep convolutional neural networks like VGG19 play a pivotal role in identifying brain lesions, ensuring robust diagnostic accuracy. Moreover, the integration of discrete wavelet- transformed images and adaptive reconstruction enhances the method's efficacy, as demonstrated through evaluation on collected brain MRI and CT images. This comprehensive approach not only facilitates enhanced diagnostic information but also accelerates the detection process crucial for preventing complications and saving lives in cases of intracranial tumors.

Furthermore, the proposed system utilizes image fusion techniques, deep learning algorithms, and transfer learning methodologies to improve brain tumor detection accuracy. Leveraging the power of multimodal image fusion and convolutional neural networks, the system surpasses traditional methods, ensuring superior performance metrics such as accuracy, precision, sensitivity, and specificity. The integration of landmark registration, discrete wavelet transforms, VGG-19 model, and watershed transform for image segmentation contributes to precise tumor localization and characterization, vital for diagnosis, treatment planning, and post- therapy monitoring. Through the seamless fusion of diverse imaging modalities and advanced computational techniques, this software tool represents a significant advancement in medical imaging technology, promising early identification and intervention for improved patient outcomes.

IV. THE PLANNING PROCESS

1. Image Registration:

The image registration phase is a crucial step in the fusion process. It involves setting up a common coordinate system to align a variety of medical imaging methods like MRI and CT scan, in order to produce a fused image that provides a more thorough and accurate representation of the tumor region.

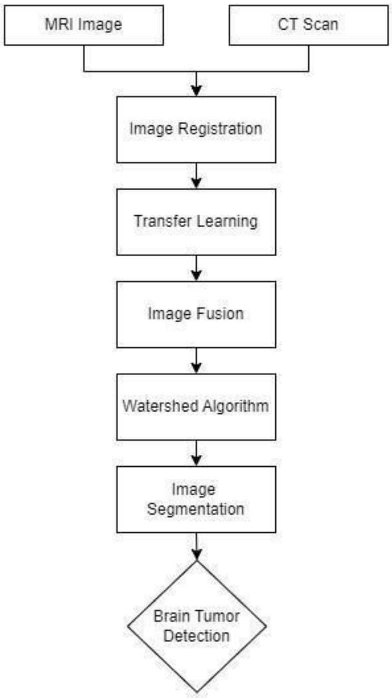

Figure 1: Flowchart

2. Landmark Registration:

It is a form of image registration technique that includes finding and lining up shared landmarks between two images. Prior to fusing the pictures, it is normal practice in medical image fusion to align the matching anatomical landmarks in the various modalities (such as MRI and CT). Finding a transformation that reduces the distance between the respective landmarks in the two images is necessary for landmark registration. Procrustes analysis, a method commonly used for accomplishing this, involves scaling, rotating, and translating one image to match the other Let W be a weight matrix that gives greater weights to more trustworthy landmarks, and let A and B be matrices that reflect the landmark points in the two images. A matrix T that represents the transformation is created by computing:

T = (B^T W A) / (A^T W A)

where ^T denotes the transpose of a matrix. This equation computes a transformation that scales, rotates, and translates the points in A to match those in B, while taking into account the weights assigned to each landmark. Once the transformation matrix is computed, it can be used to warp one image onto the other to achieve alignment.

3. Transfer Learning:

Image fusion is the process of combining multiple medical images using deep neural networks, particularly in MRI and CT images. Transfer learning is used to improve feature representation and classification precision in other images, especially when there are data shortages or noise issues in one modality. This method is used in face recognition, medical image analysis, and multispectral and hyperspectral remote sensing. In medical imaging, transfer learning is used to increase classification accuracy and reduce overfitting risk. It has also been used to improve image segmentation, such as brain tumor segmentation in MRI images. Researchers have explored transfer learning in picture fusion, with Yan et al. presenting a framework based on massive convolutional neural networks. Liu et al. (2019) reviewed transfer learning's advantages, including better feature representation, less overfitting, and quicker convergence.

4. Discrete Wavelet Transform (DWT) and its mathematical notation:

The discrete wavelet transform (DWT) has been extensively utilized in image fusion due to its ability to break down an image into its component sub bands, which represent different frequency ranges and image orientations. The DWT separates the input images into approximation and detail sub bands, which are then fused according to appropriate fusion criteria. A filter bank, which includes a collection of high-pass and low-pass filters applied to the input image at different scales and orientations, can be utilized to compute the DWT [33]. The choice of filters is often based on specific requirements, such as symmetry, orthogonality, and perfect reconstruction.
Let $h(n)$ and $g(n)$ be the low-pass and high-pass filters, and let $x\,(n, m)$ be the input picture. These formulae may be used to calculate the DWT:

Approximation coefficients:
$cA\,(j, n, m) = (h * h * x)\,(2^{-j} n, 2^{-j} m)$

Horizontal detail coefficients:
$cH\,(j, n, m) = (h * g * x)\,(2^{-j} n, 2^{-j} m)$ **Vertical detail coefficients:**
$cV\,(j, n, m) = (g * h * x)\,(2^{-j} n, 2^{-j} m)$

Diagonal detail coefficients:
$cD\,(j, n, m) = (g * g * x)\,(2^{-j} n, 2^{-j} m)$

where j is the scale of the decomposition, n and m are the spatial coordinates of the picture, and * stands for convolution. The approximation coefficients capture the low-frequency components, while the detail coefficients capture the high-frequency components. The coefficients at each level j correspond to a particular frequency range and orientation of the picture.
With each level representing a distinct scale of the image, the resultant sub bands may be arranged into a pyramidal structure. A suitable fusion rule, such as the max, min, average, or weighted average rule, can then be used to fuse the sub bands at each level.
The DWT coefficients are initially generated for the input pictures in the proposed workflow utilizing DWT and VGG-19 for image fusion, resulting in four sets of sub bands corresponding to the approximation, horizontal, vertical, and diagonal detail coefficients. After passing these sub bands through VGG-19 to extract features, each layer's output is used as a weighting element in the fusing of the associated sub bands. The weighted sub bands are combined with the proper fusion rule to produce the final fused picture.

5. VGG 19:

The VGG-19 deep convolutional neural network, developed by the Visual Geometry Group, is a powerful tool for image recognition tasks. It has 19 layers, 16 of which are convolutional, and three completely connected layers, which can recover high-level features from input images for image fusion. The network is pre-trained using supervised learning techniques and weights adjusted to minimize classification error. Each layer generates feature maps corresponding to different levels of abstraction in the input images, with lower layers capturing low-level information like edges and textures, and higher levels capturing more complex features like objects and scenes. The proposed method uses DWT coefficients and VGG-19 for image fusion, creating four sets of sub bands corresponding to horizontal, diagonal, vertical, and approximation detail coefficients. The VGG-19 formulae are based on convolutional processes, including applying filters and calculating the dot product between filter coefficients and pixel values.
Let W be the collection of weights for a certain layer in VGG-19, and let X be the input picture. The layer's output may be calculated as:
$Y = f(W * X + b)$

where b is the bias term, f is the activation function, and * stands for convolution. Gradient descent and backpropagation are used to learn the weights and bias terms during the training phase.

6. Image Segmentation:

Image segmentation is a crucial technique in medical imaging for distinguishing the edges of malignancy from healthy tissues after multimodal picture fusion for brain tumors. It gathers accurate information on the tumor's location, size, shape, and composition, which is crucial for diagnosis, treatment planning, and post-therapy monitoring. The segmentation approach enables quick classification of the tumor by determining its size, location, and features. Following multimodal image fusion, the resulting picture is processed using various image segmentation algorithms, such as edge detection, region expanding, intensity thresholding, and machine learning-based algorithms. The Watershed Transform is used for image segmentation. This technique is essential for accurately defining brain tumors and guiding therapeutic decisions.

7. Watershed Transform:

The watershed algorithm, a mathematical technique for segmenting pictures, is based on the notion of flooding a topographical area. The method assigns a height value to each pixel in the picture based on its intensity, and then by flooding the surface, separates the image into regions with local minima that act as their respective borders.[25]

A. Height function:

The height function determines the topographical surface that will be flooded by giving each pixel a height value dependent on its intensity.

$h(x, y) = -f$

Where f(XXY) is the pixel's intensity, x and y are its coordinates, and the negative sign is employed to build a basin structure for the flooding procedure.

B. Calculating the gradient:

The flooding process is guided by the gradient of the height function, which displays how rapidly nearby pixels' height values change. The gradient may be calculated using the following equations:

$Gx = (h(x + 1, y) - h(x - 1, y))/2$

$Gy = (h(x, y + 1) - h(x, y - 1))/2$

$G = sqr(Gx2, +Gy2)$

where G is the gradient's magnitude and Gx and Gee are its components in the x and y directions, respectively.

C. Calculation of flood height:

The height value utilised to flood the surface from each pixel during the flooding process is known as the flood height. The maximum of the current height and the flooding height from the surrounding pixels is the flood height [23].

$h(x, y) = \max(h(x, y), \max(h(x', y') + G(x', y'))$

where x' and y' are the coordinates of the neighboring pixels and G(x',y') is the gradient magnitude between the pixel (x,y) and its neighbor (x',y').

D. Watershed flooding:

The local minima, or the pixels with the lowest height values, are where flooding a watershed starts.
One way to describe the flooding process is as follows:

- Create a queue with the initial seeds being the local minima.
- Mark the corresponding pixel as a watershed and pop the minimum height value out of the queue.
- Calculate the flooding height using the algorithm from step 3 for each adjacent pixel that has not been processed. Add the pixel to the queue with the flooding height value as the priority if the flooding height is lower than the nearby pixel's current height.
- Up until all pixels have been processed, repeat steps 2 and 3.

E. Region merging:

Adjacent regions may over segment during the watershed flooding process and split into pixel-thin bands. These zones can be combined using a region merging technique, such as the minimum spanning tree algorithm or the watershed merging algorithm [23].

By including seed points, markers, or geographical restrictions, the basic building blocks of the watershed transform algorithm may be further improved to reduce flooding and produce more accurate segmentation results. can be combined using a region merging technique, such as the minimum spanning tree algorithm or the watershed merging algorithm[23].

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V. DEVELOPMENT TOOLS

The entire development process has been subdivided into two: the frontend development and the backend development. The front end comprises of the visually visible parts such as the home page, admin panel, contact page, shopping cart page. The back end contains the database and its interaction with the front-end.

A. Backend Development Tools

i Python: Python orchestrates the intricate dance of data, logic, and functionality, empowering seamless interactions with precision and flexibility. From handling requests to processing complex algorithms, Python's versatility fuels our system's backbone with reliability and scalability.

ii Torch: "Torch, renowned for its flexibility and efficiency, powers the backend of our project with robustness and speed, illuminating the path to seamless functionality."

iii CV2: Utilized OpenCV2 library proficiently to implement advanced image processing algorithms and computer vision techniques, enhancing the backend functionality of the project with robust visual data analysis capabilities.

iv Wavelets: Wavelets is a powerful Python library utilized in the backend of projects for efficient signal processing and wavelet transformations, offering versatile functionality for advanced data analysis and manipulation. Its robust capabilities make it indispensable for tasks requiring intricate signal decomposition and reconstruction.

B. Frontend Development Tools

i React.js: React.js, a JavaScript library for building user interfaces, is the cornerstone of the frontend development. Its component-based architecture simplifies UI development, promotes code reusability, and facilitates the creation of interactive and dynamic user interfaces for seamless user experiences.

ii Redux: Redux is employed for state management in the frontend, ensuring a predictable and centralized data flow. It helps manage the application's global state, making it easier to handle complex data interactions and maintain a consistent state across different components.

iii Axios: Axios, a promise-based HTTP client, is used for making asynchronous requests to the backend API. It streamlines data fetching and manipulation, enhancing the efficiency of communication between the frontend and backend components.

iv React Router: React Router is utilized for navigation within the single-page application. It enables the creation of dynamic, client-side routing, ensuring a seamless and intuitive user experience as users navigate through different sections of the web application.

v Visual Studio Code: Visual Studio Code serves as the integrated development environment (IDE) for frontend developers. Its extensive set of features, extensions, and debugging capabilities enhance the efficiency of the coding process and contribute to a smooth development experience.

The integrated use of these backend and frontend development tools within the MERN stack ensures a cohesive and efficient development process, allowing for the creation of a robust and feature-rich web application tailored to the needs of Mumbai University engineering students and competitive exam aspirants.

VI. TESTING AND BUG FIXING

The testing and bug-fixing phase in the development of web application stands as a crucial element in ensuring the application's reliability, functionality, and user satisfaction. Employing a systematic approach, various testing methodologies have been employed to scrutinize both individual components and the integrated system.

In the realm of unit testing, the backends' authentication system undergoes meticulous examination to verify the accuracy of user registration, login, and token generation processes. For instance, a dedicated test suite is crafted with assert statements validating the expected outcomes, ensuring the robustness of our authentication mechanisms.

Moving to the realm of integration testing, scenarios involving the interaction between frontend and backend components are thoroughly examined. For instance, the end-to-end book transaction process is scrutinized to ensure that data is seamlessly transferred between the client and server, and that transactions are securely processed.

User Acceptance Testing (UAT) serves as the ultimate validation, bringing actual users into the testing process. This real-world evaluation allows us to assess how well the application meets end-users' expectations and requirements. Feedback from UAT has been instrumental in refining our user interface, enhancing navigation, and optimizing overall user interactions.

Throughout this testing journey, identified issues and bugs are diligently documented, categorized, and prioritized based on their impact. Adopting an agile bug-fixing approach ensures swift resolution of critical issues. Feedback from user testing and UAT is then integrated into our iterative development process, contributing to the continuous improvement of the application. This holistic testing and bug-fixing approach guarantee the creation of a reliable, user-friendly MERN stack web application tailored to the specific needs of Mumbai University engineering students and competitive exam aspirants.

VII. RESULT

The culmination of the development efforts and rigorous testing has yielded compelling results, affirming the success and impact of the MERN stack web application for Mumbai University engineering students and competitive exam aspirants. Key performance indicators, user feedback, and system metrics collectively highlight the positive outcomes of this endeavour.

The platform's e-commerce functionality played a pivotal role in facilitating seamless transactions between users, enabling the exchange of previous semester books at reasonable prices. User feedback highlighted satisfaction with the streamlined checkout process and the integration of secure online payment gateways.

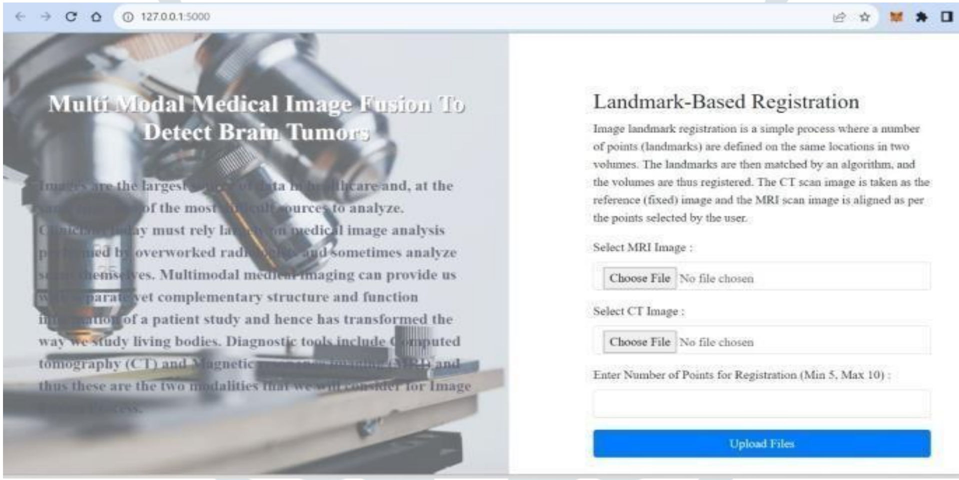

Figure 1: Home Page.

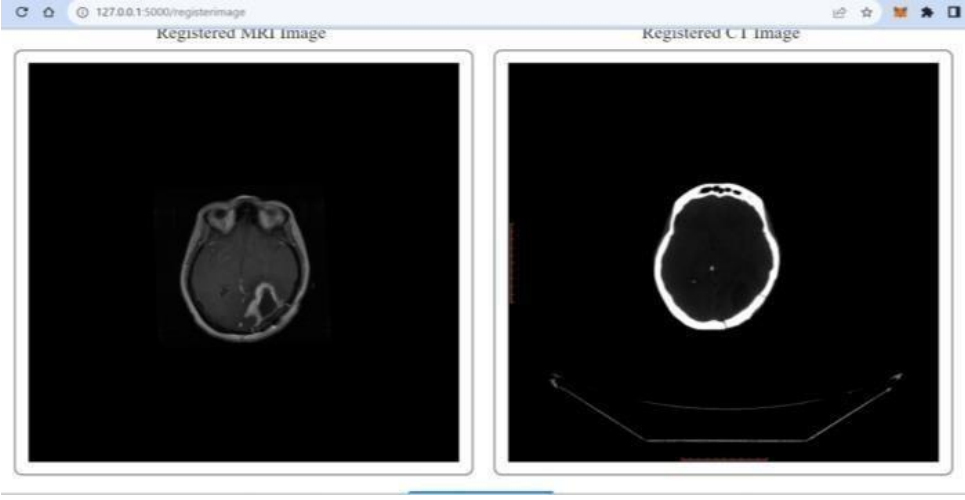

Figure 2: Registered MRI and CT Images Provided by the user.

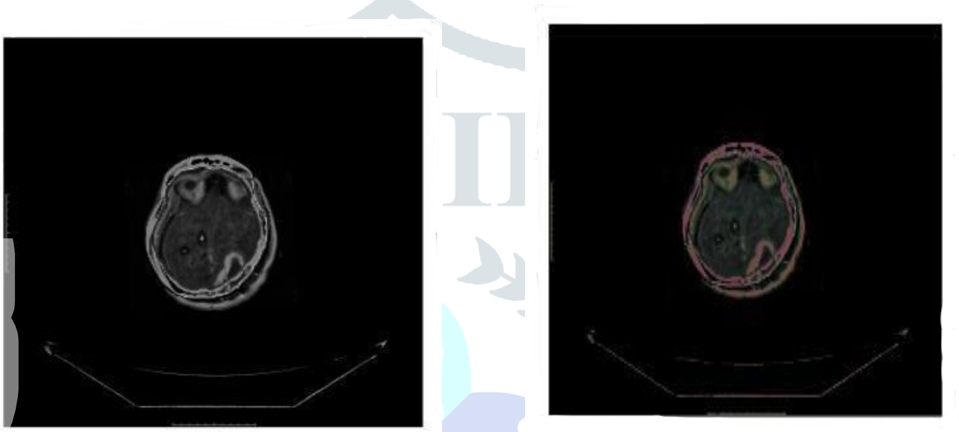

Figure 3. Fused Image and Image formed on Segmentation

Model	Precision	Sensitivity	Specificity	Accuracy
VGG16	88.23	93.75	94.12	94
VGG19	100	94.73	100	98
DenseNet121	85.71	100	94.73	96
DenseNet201	93.33	93.33	97.14	96

Table 1: Confusion Matrix parameters with 16 batch sizes for all models.

FUTURE GOALS

Looking ahead, the trajectory of our MERN stack web application involves a roadmap focused on continuous improvement and strategic expansion. Future goals span diverse areas, all aimed at elevating the functionality, reach, and impact of the platform to serve the evolving needs of Mumbai University engineering students and competitive exam aspirants.

In terms of feature enrichment, vision includes implementing an advanced recommendation system that tailors suggestions based on individual user preferences, academic history, and popular choices within the platform. Additionally, researcher can enhance user profiles, allowing users to showcase their academic achievements, contribute to community discussions, and provide valuable insights.

Geographic expansion is a key facet of our future goals, with plans to forge partnerships with other universities and educational institutions. This expansion will not only broaden our user base but also facilitate collaboration and resource sharing on a larger scale. Implementing localization features and multilingual support is also on the agenda to cater to students from diverse linguistic backgrounds.

The integration of emerging technologies is a pivotal aspect of forward-looking strategy. Exploring the incorporation of augmented reality (AR) for book previews aims to provide users with interactive experiences before making a purchase. Additionally, the investigation into blockchain technology for transaction security underscores our commitment to ensuring the utmost transparency and integrity in online transactions.

VIII. Conclusion

The use of image fusion has significantly increased in recent years across a range of image processing applications, particularly in the medical field for the segmentation of retinopathy and brain tumors.
The multimodal medical image fusion for the images of the brain from CT and MRI using VGG-19 algorithms is presented in the study. The proposed VGG-19 beats competing algorithms on a variety of performance metrics. The accuracy and interpretability of brain tumor imaging data might be enhanced by multimodal image fusion approaches. Since certain tumors may not be apparent on a single imaging modality but may be recognized when numerous modalities are fused together, it significantly lowers the likelihood of false-positive or false-negative diagnosis. As a result, patients' prognosis and quality of life may be improved by early identification and treatment.

IX. Acknowledgements

We respect and thank HOD Rd. Uttara Gogate & Prof. Pallavi Harambe along with our principal Rd. Pramod Rodge for providing us an opportunity to optimize the project work in SSJCOE Dombivli and providing us all support and guidance which made us pursue the project duly. We are extremely thankful to them for providing such nice support and guidance. We are with our deep gratitude to our project guide Prof. Pallavi Harambe, who took keep interest in our project work and guided us all along by providing all the necessary for developing a good system.

We are thankful to and fortunate enough to get constant encouragement, support and guidance from all Teaching staff of Computer Engineering which helped us in pursuing our project work.

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