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Survey On Brain Tumor Prognosis Using Deep Learning

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ABSTRACT

Accurate brain tumor type classification is very important for timely diagnosis and treatment planning. Therefore, it improves the outcomes of the patients. MRI is a noninvasive imaging technique that has been widely employed to generate highcontrast grayscale images of brains for diagnosing tumors. Recently, much progress has been achieved with the development of deep learning, especially CNNs, in improving the diagnostic accuracy in medical imaging. In this work, a transfer learning-based approach is adopted where several deep learning models are being fine-tuned to classify brain tumors on a three-class classification problem, namely glioma, meningioma, and pituitary tumors.

1. INTRODUCTION

The early and accurate detection of brain tumors is crucial for effective prognosis and treatment planning. Brain tumors, such as gliomas, meningiomas, and pituitary tumors, pose significant health challenges due to their location and impact on essential brain functions. Magnetic Resonance Imaging (MRI) plays a vital role in diagnosing these conditions, generating vast amounts of data that can be leveraged using advanced artificial intelligence (AI) techniques[1]. Deep Learning(DL) particularly convolutional neural networks(CNNs), has revolutionized medical imaging by enabling automated and highly accurate image classification. These techniques, combined with transfer learning models such as VGG16, VGG19, EfficientNet, and InceptionV3, have shown remarkable potential in classifying brain tumors with high precision. By analyzing MRI data, AI can assist healthcareprofessionals in identifying tumor types, tracking disease progression, and tailoring treatment plans. This review explores the application of deep learning models for automatic biomedical image classification in brain tumor prognosis, highlighting their performance, challenges, and the future of AI-driven healthcare[2].

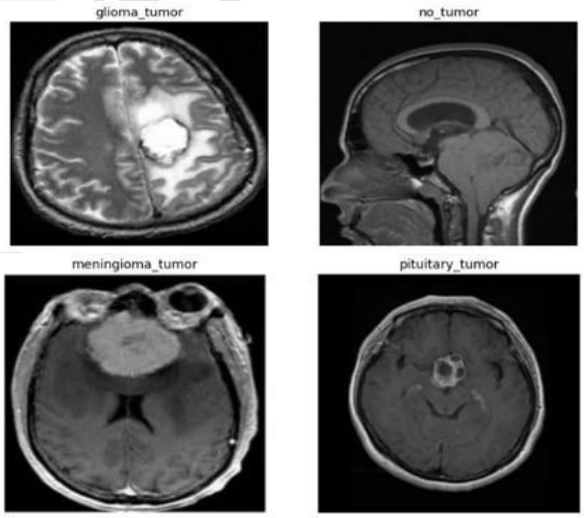

figure1: Types of tumors

Brain tumors are abnormal growths of cells in the brain or Central Nervous System(CNS) that can vary significantly in their nature, aggressiveness, and treatment options. Gliomas are the most common type of primary brain tumor, originating from glial cells in the brain or spinal cord. Glial cells provide structural support, protection, and nutrition to neurons, the primary cells responsible for transmitting nerve signals. Gliomas can vary

widely in terms of their growth rate, aggressiveness, and prognosis, depending on the specific type of glial cell they arise from and their biological characteristics. Meningiomas are the most common type of primary brain tumor, accounting for approximately 30% of all brain tumors. They originate from the meninges, which are the protective membranes that cover the brain and spinal cord. Meningiomas are typically benign (non-cancerous) and slow-growing, but they can still cause significant neurological symptoms due to their location and size. In some cases, meningiomas can become atypical or maligenant (cancerous), leading to more aggressive behavior and a worse prognosis. pituitary tumors are abnormal growths that develop in the pituitary gland, a small, pea-sized gland located at the base of the brain. The pituitary gland is often referred to as the "master gland" because it produces hormones that regulate critical functions in other endocrine glands, such as the thyroid, adrenal glands, and reproductive organs[3]. While most pituitary tumors are benign (noncancerous), their location and the hormones they affect can lead to significant health problems. These
tumors can cause symptoms by either secreting excess hormones or pressing on nearby structures, such as the optic nerves.

2. IDENTIFICATION OF BRAIN TUMOR

Magnetic Resonance Imaging (MRI) is one of the most effective and widely used imaging modalities for identifying brain tumors. It provides detailed images of brain structures and is crucial for diagnosis, treatment planning, and monitoring. The main principle of MRI employs strong magnetic fields and radio waves to generate high-resolution images of the brain. Unlike CT scans, MRI does not use ionizing radiation, making it safer for repeated use, especially in patients requiring ongoing monitoring.[1]

2.1. MACHINE LEARNING BASED METHODS FOR BRAIN TUMOR DETECTION

Machine learning (ML) techniques have been widely applied in the identification and diagnosis of brain tumor using medical imaging data, particularly MRI scans. Unlike deep learning, which automatically learns features from raw data, traditional machine learning methods often require feature extraction before model training. Machine learning-based methods have demonstrated strong potential in brain tumor detection by providing effective classification and segmentation models. Techniques such as Support Vector Machines, Random Forests, and Decision Trees have been widely applied to MRI-based tumor detection, leveraging handcrafted features to drive accurate predictions. These methods offer a balance between interpretability and performance, making them valuable in clinical decision-making[4].

2.1.1 SUPPORT VECTOR MACHINE(SVM)

Support Vector Machines (SVM) are widely used in brain tumor prognosis for classifying tumor types, assessing malignancy, and predicting survival or recurrence. They analyze features extracted from medical imaging data like MRI, such as tumor size, shape, and texture[3]. SVM models are trained on labeled datasets to distinguish between benign and malignant tumors, aiding in treatment planning. They can also predict survival rates and the likelihood of tumor recurrence based on clinical and imaging data. Additionally, SVM can integrate multimodal data (e.g., MRI, PET scans, and genetic information) to improve prediction accuracy. While SVM offers high accuracy and robustness, it requires careful feature selection and may struggle with imbalanced data. Its "black box" nature can limit interpretability, making it harder to understand how predictions are made. Despite challenges, SVM remains a powerful tool for personalized brain tumor prognosis.

2.1.2 RANDOM FOREST (RF)

Random Forest (RF) is widely used in brain tumor prognosis for classification, grading, and survival prediction. It builds multiple decision trees using subsets of data and features, making predictions based on the majority vote or average of these trees. RF can classify tumor types (e.g., gliomas, meningiomas) by analyzing imaging features like size, shape, and texture. It is also used for distinguishing between low-grade and high-grade tumors, aiding in malignancy assessment. RF helps predict survival rates by analyzing clinical and imaging data, categorizing patients into risk groups[5]. It can also predict tumor recurrence after treatment. RF is effective in handling multimodal data, combining imaging and clinical information for better accuracy. The algorithm's robustness to noise and overfitting makes it suitable for complex medical datasets. Its ability to process large numbers of features improves prediction reliability. Overall, Random Forest provides accurate, stable, and interpretable results for brain tumor prognosis.

2.1.3 K-NEAREST NEIGHBORS

K-Nearest Neighbors (KNN) is a simple, yet effective, machine learning algorithm used for brain tumor prognosis by classifying tumor types and predicting outcomes based on medical data. KNN works by identifying the 'K' closest data points (neighbors) to a given instance and classifying the instance based on the majority class of those neighbors. For brain tumor prognosis, KNN can classify tumor types (e.g., gliomas, meningiomas) by analyzing features from MRI or CT scans, such as tumor size, shape, and texture. KNN can also differentiate between benign and malignant tumors by comparing their characteristics to known labeled data[4]. Additionally, KNN can predict the likelihood of survival or recurrence by considering clinical and imaging features. KNN is non-parametric, meaning it doesn't make assumptions about the underlying data distribution, making it flexible for complex datasets. However, it can be computationally expensive with large datasets, as it requires calculating distances between all data points. Proper feature scaling is necessary for KNN to work effectively, as it is sensitive to the scale of data. Choosing the optimal number of neighbors (K) is crucial for balancing accuracy and overfitting. Despite its simplicity, KNN provides useful, interpretable results for brain tumor prognosis.

2.1.4 NAÏVE BAYES CLASSIFIER

Naive Bayes classifier can be used for brain tumor prognosis by applying probabilistic models to classify tumor types or predict outcomes based on medical data. It works by assuming that features are independent given the class label, making it computationally efficient. For brain tumor prognosis, features extracted from MRI or CT scans, such as tumor size, shape, and texture, are used to calculate probabilities for different tumor types (e.g., gliomas, meningiomas). Naive Bayes estimates the likelihood of a tumor being malignant or benign by considering the distribution of features in each class. It can also predict survival or recurrence by classifying patients into risk groups based on clinical and imaging data. The algorithm is particularly effective when there is limited data and is easy to interpret. Naive Bayes is fast and works well with small to medium-sized datasets but may struggle with correlated features. Feature selection is important to improve model performance, as the independence assumption may not hold for all features[6][7]. Despite its simplicity, Naive Bayes can provide accurate results for brain tumor prognosis, especially in conjunction with other models.

2.1.5 DECISION TREES

Decision Tree (DT) can be used for brain tumor prognosis by creating a model that splits data into branches based on feature values, ultimately leading to a classification or prediction. For brain tumor prognosis, decision trees can classify tumor types (e.g., gliomas, meningiomas) or predict tumor malignancy (benign vs. malignant) based on features like size, shape, and texture from MRI or CT scans. The tree structure makes it easy to visualize decision-making and understand the relationship between features and outcomes. DT can also predict survival rates or recurrence by analyzing clinical and imaging data, dividing patients into risk groups. It handles both categorical and numerical data effectively and requires little data preprocessing. However, decision trees are prone to overfitting, so pruning techniques or ensemble methods like Random Forest may be applied to improve generalization. The interpretability of decision trees is a significant advantage in clinical settings, allowing doctors to understand how predictions are made. DT models can be used for both classification and regression tasks, making them versatile for prognosis. Proper feature selection and data preparation are essential for optimal performance[7]. Overall, decision trees provide a straightforward, interpretable tool for brain tumor prognosis.

2.2 DEEP LEARNING BASED METHODS FOR BRAIN TUMOR INDENTIFICATION

In recent years, deep learning has revolutionized medical imaging, including the identification and diagnosis of brain tumors. Deep learning techniques, especially CNN have demonstrated remarkable success in analyzing complex brain MRI images, enabling accurate tumor detection, segmentation, and classification[7]. These methods have shown potential to improve diagnosis, treatment planning, and monitoring of brain tumors.

2.2.1CONVOLUTIONAL NEURAL NETWORKS (CNNs)

Convolutional Neural Networks (CNNs) are highly effective for brain tumor prognosis, especially in analyzing medical images like MRI or CT scans. CNNs automatically extract spatial features from images by applying convolutional layers, which detect patterns such as tumor shape, texture, and edges. For brain tumor prognosis, CNNs can classify tumor types (e.g., gliomas, meningiomas) and predict tumor malignancy (benign vs. malignant) by learning from large datasets of labeled images. CNNs can also predict survival or recurrence by analyzing imaging features in combination with clinical data[8]. The network is trained by feeding images into the model, which learns hierarchical feature representations at different layers. Data augmentation techniques like rotation, zoom, and flipping help improve model generalization and prevent overfitting. CNNs are capable of handling large, high-dimensional image data, making them suitable for complex medical imaging tasks. Transfer learning, where pre-trained models are fine-tuned on specific tumor datasets, can further enhance performance[19]. The model's accuracy improves with more data, making CNNs particularly useful for large-scale prognosis tasks. Overall, CNNs provide powerful, automated, and accurate predictions for brain tumor prognosis.

2.2.1.1 EFFICIENT NET

EfficientNet can be used for brain tumor prognosis by leveraging its efficient architecture for analyzing medical images like MRI or CT scans. It is a deep learning model that scales up in a more efficient manner compared to traditional CNNs, balancing depth, width, and resolution to optimize performance. For brain tumor prognosis, EfficientNet can be trained to classify tumor types (e.g., gliomas, meningiomas) or predict tumor malignancy (benign vs. malignant) by extracting relevant features from imaging data. It can also predict survival rates or tumor recurrence by analyzing imaging features alongside clinical data. EfficientNet's lightweight design and fewer parameters enable faster training and inference, making it suitable for large-scale datasets[9]. Transfer learning can be applied by fine-tuning pre-trained EfficientNet models on brain tumor-specific datasets, enhancing model accuracy. The model's ability to handle complex features in medical imaging makes it suitable for high-dimensional tasks like tumor segmentation and classification. Data augmentation, such as rotation and scaling, can further improve model generalization. EfficientNet is known for its superior performance and efficiency in medical image analysis tasks. Overall, it provides an accurate, fast, and resource-efficient approach to brain tumor prognosis.

2.2.1.2 RESIDUAL NETWORKS

ResNet (Residual Networks) can be used for brain tumor prognosis by analyzing medical images such as MRI or CT scans. Its key feature is the use of residual blocks, which allow the model to train deeper networks by mitigating the vanishing gradient problem. For brain tumor prognosis, ResNet can classify tumor types (e.g., gliomas, meningiomas) or predict malignancy (benign vs. malignant) by learning from features like tumor shape, texture, and intensity. The deep architecture of ResNet enables it to capture complex patterns in high-dimensional medical images. Transfer learning can be applied by fine-tuning pre-trained ResNet models on brain tumor datasets, improving accuracy with limited data[10]. ResNet can also predict survival outcomes or recurrence based on imaging features combined with clinical data. Data augmentation techniques such as rotation, flipping, and zooming help improve generalization and prevent overfitting. ResNet's robustness to overfitting and its ability to handle large-scale datasets make it ideal for brain tumor prognosis tasks[18]. The model's performance improves with deeper layers, allowing it to handle more complex imaging data. Overall, ResNet provides an effective, high-accuracy approach to brain tumor prognosis and classification.

2.2.2 GENERATIVE ADVERSARIAL NETWORKS(GANs)

Generative Adversarial Networks (GANs) can be used in brain tumor prognosis by generating synthetic medical images and enhancing the training of predictive models. GANs consist of two networks: a generator that creates synthetic data (e.g., MRI images) and a discriminator that evaluates the authenticity of generated images. In brain tumor prognosis, GANs can generate high-quality, labeled imaging data to augment limited datasets, improving model performance. They can also be used for tumor segmentation, helping in precise delineation of tumor boundaries in MRI scans. GANs can simulate different tumor types or variations, providing diverse data for training classification models[11]. Additionally, GANs can aid in improving other models like CNNs by generating realistic samples that increase generalization. For prognosis, GAN-generated images can be used to train classifiers to predict tumor type, malignancy, or recurrence risk. Transfer learning with pre-trained GAN models on medical datasets can further boost performance. GANs help address the issue of data scarcity by generating new examples, especially in rare or less-represented tumor cases. Overall, GANs offer a novel approach to enhancing image data and improving the accuracy of brain tumor prognosis models.

2.2.3 TRANSFER LEARNING

Transfer learning can be used for brain tumor prognosis by leveraging pre-trained models on large, general datasets and fine-tuning them on specific brain tumor datasets. This approach saves time and computational resources by taking advantage of the feature representations learned from a large dataset (e.g., ImageNet) and adapting them to brain tumor classification tasks. For brain tumor prognosis, a pre-trained model like ResNet, EfficientNet, or VGG can be fine-tuned on MRI or CT scan images with labeled tumor data (e.g., benign vs. malignant). The model's convolutional layers, which capture low-level features like edges and textures, can be retained, while the fully connected layers are adjusted to classify tumor types or predict survival and recurrence. Transfer learning is particularly useful when limited labeled data is available for brain tumor prognosis. It allows the model to generalize better, as it has already learned useful patterns from a broader dataset. Data augmentation techniques like rotation and flipping help improve generalization further. Transfer learning reduces the need for large amounts of labeled tumor data, making it practical for medical applications[12]. The method improves accuracy, speeds up model training, and ensures high performance for brain tumor classification and prognosis. Ultimately, transfer learning enhances the ability to predict tumor malignancy, survival, and recurrence.

2.2.3.1 FINE TUNING

Fine-tuning can be used for brain tumor prognosis by taking a pre-trained model and adjusting it for specific tasks related to brain tumor classification and prediction[13]. Typically, a model like ResNet, EfficientNet, or VGG, pre-trained on large datasets (e.g., ImageNet), is adapted for tumor-related tasks using brain MRI or CT scan data. The earlier layers of the model, which capture low-level features such as edges and textures, are generally frozen, while the deeper layers are fine-tuned to better detect tumor-specific features, such as size, shape, and intensity. Fine-tuning involves training the model on a smaller, task-specific dataset (e.g., benign vs. malignant tumors), updating only the parameters in the final layers or specific layers relevant to the task. This approach is particularly useful when limited labeled data is available for brain tumor prognosis. It speeds up training, improves accuracy, and reduces the risk of overfitting. Fine-tuning allows the model to leverage the general knowledge learned from large datasets and adapt it to the brain tumor domain. The model can predict tumor types, malignancy, and survival outcomes. Fine-tuning improves the model's performance and generalization capability for clinical tasks, such as predicting tumor recurrence. Overall, fine-tuning enhances model efficiency, accuracy, and relevance in brain tumor prognosis[14].

2.2.3.2. FEATURE EXTRACTION

Feature extraction for brain tumor prognosis involves identifying and extracting meaningful patterns from medical images like MRI or CT scans to make accurate predictions. Key features such as tumor size, shape, texture, edge, intensity, and location are extracted from the images to be used in predictive models. Common techniques include statistical methods (e.g., histogram analysis), texture analysis (e.g., GLCM), and geometric methods to capture the tumor's structural and morphological characteristics. These features are then used as input to machine learning models like SVM, Random Forest, or neural networks to classify tumor types (benign vs. malignant) or predict survival and recurrence[15]. Feature extraction can also combine clinical data (e.g., age, gender, genetic markers) to improve prognosis. The extracted features help reduce the complexity of raw image data, making it more manageable for the model. Preprocessing steps like normalization or scaling ensure that features are on the same scale for accurate model training. Feature selection techniques, such as principal component analysis (PCA), may be used to reduce dimensionality and enhance model performance. Effective feature extraction is critical for improving the accuracy and interpretability of brain tumor prognosis models[17]. Ultimately, this method helps provide precise and personalized predictions for tumor diagnosis and treatment planning.

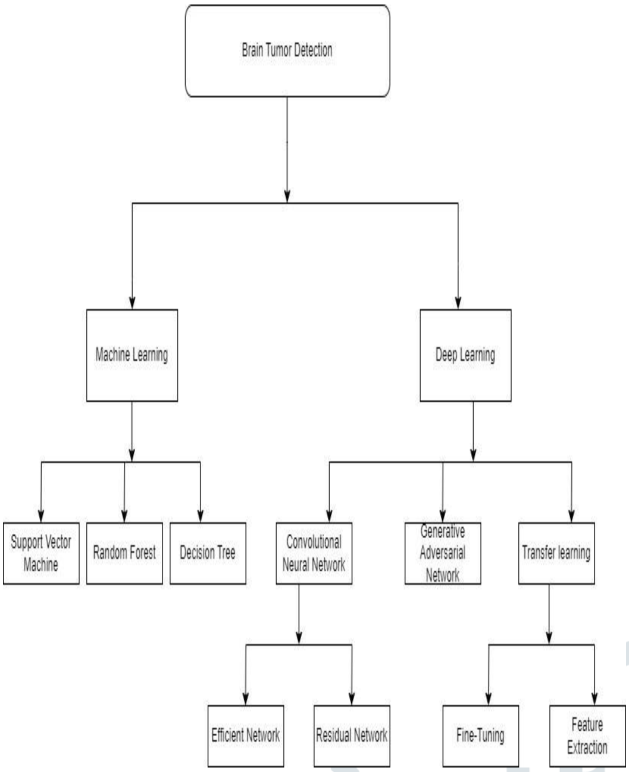

Figure2: Classification of AI Techniques for Brain Tumor Detection

3.DATASET:

CATEGORY	150*150	240*240	300*300	MEMORY SIZE	REFERENCE LINK
Glioma	320	258	348	1.8 GB	https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri/data
Meningioma	128	235	137	800 MB	https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri/data
Pituitary	338	280	319	1.6 GB	https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri/data
No Tumor	239	240	242	1.3 GB	https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri/data

Description for Dataset:

The dataset focuses on brain tumor analysis and classification, including categories such as Glioma, Meningioma, and Pituitary. It consists of medical images organized into three resolutions: 150×150, 240×240, and 300×300. These variations in resolution enable researchers to study the effect of image quality on diagnostic and classification performance. The dataset also records the memory size associated with each resolution, ranging from smaller sizes like 800 MB to larger ones like 1.8 GB, providing insights into computational requirements. This dataset is particularly valuable for training machine learning models aimed at detecting and classifying brain tumors. It can aid in developing automated diagnostic tools, improving the accuracy of tumor detection, and enhancing the performance of existing algorithms in medical imaging research.

4. Literature Survey

Models	Dataset	Method	Accuracy	Reference
Hybrid Deep CNN Model (2023)	BraTS, custom datasets	Combines Grey Wolf Optimizer (GWO) with Faster R-CNN for feature extraction and dimensionality reduction.	98%	https://bmcmedimaging.biomedcentral.com/articles/10.1186/s12880-023-00829-7
PCA-NGIST + RELM (2023)	Cheng Dataset (3064 images)	Preprocessing using PCA-NGIST descriptors followed by classification with Regularized Extreme Learning Machine (RELM).	94.23%	https://bmcmedinformdecismak.biomedcentral.com/articles/10.1186/s12911-023-02056-3
YOLOv5-Based Object Detection (2023)	BraTS 2021	Applied YOLOv5 for efficient tumor detection, focusing on computational speed.	88%	https://bmcmedimaging.biomedcentral.com/articles/10.1186/s12880-023-00829-7
MIDNet18 (2023)	Custom Dataset	Deep CNN architecture tailored for binary tumor classification, emphasizing medical image analysis.	>98%	https://bmcmedimaging.biomedcentral.com/articles/10.1186/s12880-023-00829-7

SVM with Gaussian Kernel (2022)	Custom MRI Dataset	SVM with L1NSR Feature Selection	Classification accuracies of 98.8% and 96.6%.	https://bmcmedimaging.biomedcentral.com/articles/10.1186/s12880-024-01323-3
ECOC-SVM + CNNs (AlexNet, VGG-16, VGG-19) (2022)	BraTS, RIDER MRI	CNNs for feature selection, combined with ECOC-SVM for tumor classification. AlexNet outperformed others.	99.55%	https://bmcmedinformdecismak.biomedcentral.com/articles/10.1186/s12911-023-02056-3
EfficientNet V2 + Ranger Optimizer (2022)	Kaggle Brain MRI Dataset	Used EfficientNetV2 with optimized pre-processing and Ranger optimizer for enhanced efficiency.	98.9%	https://bmcmedimaging.biomedcentral.com/articles/10.1186/s12880-023-00829-7
Deep CNNs for Tumor Classification (2023)	Custom Dataset	Voting Classifier with Logistic Regression & SGD	Achieved 99.9% accuracy using deep convolutional features.	https://bmcmedimaging.biomedcentral.com/articles/10.1186/s12880-024-01323-3
IVX16 Model with Explainable AI (2023)	Kaggle Dataset	Combination of VGG16, InceptionV3, ResNet50	Peak accuracy of 96.94%. Used explainable AI for reliability assessment.	https://bmcmedimaging.biomedcentral.com/articles/10.1186/s12880-024-01323-3
Hybrid DL with Attention Models (2022)	Public MRI Dataset	Fusion of ResNet, InceptionV3, and ShuffleNet	Achieved 99.7% accuracy in multi-class classification.	https://bmcmedimaging.biomedcentral.com/articles/10.1186/s12880-024-01323-3
Spatial Pyramid Matching (2020)	Augmented CE-MRI Dataset	Spatial Pyramid Matching with Ring-form Partitioning	Enhanced classification accuracy using GLCM and BoW features.	https://bmcmedimaging.biomedcentral.com/articles/10.1186/s12880-024-01323-3

5. CONCLUSION

Brain tumor classification and detection highlights significant advancements in applying deep learning techniques to medical imaging. Recent studies emphasize the dominance of convolutional neural networks (CNNs) and transfer learning models like EfficientNet, ResNet, and hybrid approaches combining models such as ResNet and ShuffleNet. Accuracy levels often exceed 90%, with some studies achieving up to 99% using ensemble methods and data augmentation. Public datasets such as BraTS, Kaggle MRI, and Figshare serve as benchmarks for these methods. However, challenges like limited dataset sizes, computational complexity, and translating models to clinical applications persist[20]. Innovations like explainable AI, attention mechanisms, and spatial pyramid matching enhance model interpretability and performance, paving the way for reliable deployment in healthcare. Future research should focus on synthetic data generation, lightweight models, and collaborations between AI researchers and medical professionals to bridge the gap between research and clinical utility.

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