CS6611

LITERATURE SURVEY

Brain Tumour Segmentation

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| Title | Author | Year | Methodology | Advantages | Setbacks |
| An enhanced deep learning approach for brain cancer MRI images classification using residual networks | S. A. A. Ismael, A. Mohammed, and H. Hefny | 2020 | Residual Networks (ResNets): This type of deep learning architecture uses residual connections, which help address the vanishing gradient problem and allow deeper networks to learn effectively.  Brain Cancer MRI Images Classification: The research likely trained a ResNet model on labeled brain cancer MRI images to classify them into different types (e.g., glioma, meningioma).  Enhanced Deep Learning Approach: This suggests the authors might have incorporated specific techniques to improve the ResNet model's performance, such as transfer learning, data augmentation, or specialized loss functions. | High accuracy: ResNets have shown success in various image classification tasks, potentially achieving high accuracy in classifying brain cancer types.  Reduced training time: Residual connections can improve training efficiency compared to standard CNNs.  Improved generalizability: Enhanced techniques like data augmentation might help the model generalize better to unseen data. | Data limitations: Access to high-quality, labeled brain cancer data can be limited, hindering model performance.  Overfitting: Careful tuning of hyperparameters is crucial to avoid overfitting the model to the training data.  Interpretability: Deep learning models can be challenging to interpret, raising concerns about understanding their decision-making process. |
| Brain tumour detection from images and comparison with transfer learning methods and 3-layer CNN | Mohammad Zafer Khaliki & Muhammet Sinan Başarslan | 2024 | Dataset: The dataset consists of 2870 human brain MRI images classified into four categories  Model Selection: Utilizes Convolutional Neural Network (CNN) architecture and transfer learning methods (InceptionV3, VGG16, VGG19, EfficientNetB4).  Evaluation Metrics: F-score, recall, precision, and accuracy are used to evaluate the models.  Approach: Investigates the performance of CNN and transfer learning on brain images, comparing CNN as a multi-layer without transfer learning. | High Accuracy: Achieves a best accuracy result of 98% with VGG16, showcasing the effectiveness of transfer learning and CNNs in brain tumor classification.  Early Diagnosis: AI technologies like CNNs and transfer learning can aid in early diagnosis and rapid treatment of brain tumours. | Computational Resources: Training complex models like transfer learning architectures may require significant computational resources.  Dataset Quality: Achieving good results with a skewed and poor-quality dataset may be challenging and require additional preprocessing or data augmentation. |

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| Artificial Intelligence in Bone Metastases: An MRI and CT Imaging Review | Eliodoro Faiella , Domiziana Santucci , Alessandro Calabrese , Fabrizio Russo , Gianluca Vadalà , Bruno Beomonte Zobel , Paolo Soda , Giulio Iannello , Carlo de Felice and Vincenzo Denaro | 2022 | MEDLINEdatabases, such as PubMed and Web of Science, were employed for the research, using the following strings: ((“radiomics” OR “machine learning”) AND (metas tases OR metastasis) AND (“bone” OR “spine” OR “spinal”)).The following criteria were used for the inclusion of the studies: (a) imaging analysis involved only CT and MRI modalities; (b) the studies addressed the ability of radiomics to predict, diagnose, or characterize bone lesions; (c) the studies involved humans only; (d) the articles were accessible through our institution; and (e) the publications were in English. | Four different machine learning classifiers were de veloped and compared, with logistic regression outperforming the others. The nomogram achieved an AUC of 0.821 (SEN = 0.667, SPE = 0.909): DCA showed that the nomogram had a higher net benefit than all treatment.  The radiomics MRI model combined with clini copathological features (free PSA level, age, and Gleason score) yielded the highest AUC (AUC=0.916), further improving predictive performance. | All articles included among their limitations the relatively small sample size (<200 patients), the single-center nature of the study, and the selection bias introduced by the retrospective design.Some articles complained about the tediousness of manual segmentation, which, in addition to being time-consuming, is not free of human error. Our review confirms the considerable heterogeneity in current radiomics research, as evidenced by the relatively low RQS value obtained when analyzing the reviewed studies (22.6%). |
| Brain Tumor Segmentation from MRI Images Using Handcrafted Convolutional Neural Network | Faizan Ullah, Muhammad Nadeem, Mohammad Abrar, Muna Al-Razgan, Taha Alfakih, Farhan Amin, Abdu Salam | 2023 | Data Preparation: Used BraTS 2018 MRI dataset, preprocessed for alignment, skull stripping, intensity normalization, and bias field correction.  Feature Extraction: Extracted Dense SURF (DSURF) and Histogram of Oriented Gradients (HOG) features.  CNN Architecture: Employed a U-Net-based CNN for segmentation, capturing context and enabling precise localization.  Training: Trained the CNN with cross-entropy and Dice coefficient losses, using stochastic gradient descent (SGD) with momentum and early stopping to prevent overfitting.  Feature Integration: Integrated handcrafted features into the CNN using input channel, feature map, and decision level fusion.  Fine-Tuning: Fine-tuned the CNN to adapt to the new input representation, with a reduced learning rate and fewer epochs.  Evaluation: Evaluated performance using segmentation accuracy, Dice score, sensitivity, and specificity. | Enhanced Performance: Outperformed traditional methods and individual CNN approaches for brain tumor segmentation.  Robustness: Integration of handcrafted features improved the CNN's robustness and generalizability. | Complexity: Integrating handcrafted features adds complexity and requires careful tuning.  Data Needs: CNNs, especially with handcrafted features, require large, annotated datasets.  Computational Demands: CNNs can be computationally expensive, needing powerful hardware or cloud resources.  Interpretability: CNNs' black-box nature can make interpreting decisions challenging. |
| Application of Artificial Intelligence Methods for Imaging of Spinal Metastasis | Wilson Ong , Lei Zhu , Wenqiao Zhang , Tricia Kuah , Desmond Shi Wei Lim , Xi Zhen Low , Yee Liang Thian , Ee Chin Teo , Jiong Hao Tan , Naresh Kumar , Balamurugan A. Vellayappan , Beng Chin Ooi , Swee Tian Quek , Andrew Makmur and JamesThomasPatrickDecourcy Hallinan | 2022 | Asystematic, detailed literature search of the main electronic medical databases was undertaken in concordance with the PRISMA guidelines.. Databases were searched for the following terms: (“spinal” OR “vertebral”) AND (“metastasis” OR “metastases”) AND (“radiomics”, OR“machine learning”, OR “deep learning”, OR “artificial intelligence”)Other inclusion criteria included the following: (a) imaging analysis involving nuclear medicine studies, CT and/or MRI scans; (b) studies addressing the capacity to predict, diagnose and integrate the deep learning into clinical practice | Their radiomics model was effective in predicting progressive vs non progressive disease with an area under the curve (AUC) of up to 0.91.Their study concluded that the model was the most effective in predicting response to pain following radiotherapy with an AUC of 0.85 and accuracy of 82.6%, when comparing clinical features with an AUC of 0.70 and accuracy of 65.2%.The combined radiomics/clinical model showed good performance with sensitivity of 84.4%, specificity of 80.0% and AUC of 0.88, exceeding the performance of clinical features alone. | Pseudo-progression is a post-treatment phenomenon involving an increase in the tar get tumour volume (usually without any worsening symptoms), which then demonstrates interval stability or reduction in volume on repeat imaging. It occurs in approximately 14 to 18%ofthosewithvertebralmetastasestreated with stereotactic body radiotherapy The differentiation of pseudo-progression from true progression is challenging on imaging even with many studies suggesting some differentiating factors [161,162], such as location of involvement, e.g., purely vertebral body. |
| Brain tumor detection and classification: A framework of marker-based watershed algorithm and multilevel priority features selection | M. A. Khan, I. U. Lali, A. Rehman, M. Ishaq, M. Sharif, T. Saba, S. Zahoor, and T. Akram | 2019 | Utilizes a marker-based watershed algorithm to segment brain tumors from MRI images. This algorithm relies on identifying seed points within the tumor and progressively expanding areas with similar intensity values.  Employs multilevel priority features selection to extract relevant features from the segmented tumor region. This likely involves filtering and ranking features based on their effectiveness in differentiating tumor types.  Classifies tumors into different categories using a statistical learning method. | Watershed algorithm effectively isolates tumor regions from surrounding healthy tissue.  Multilevel features selection enhances the distinctiveness between tumor types, potentially improving classification accuracy.  Offers an automated and potentially less subjective approach compared to manual tumor segmentation. | Watershed algorithm's performance can be sensitive to noise and intensity variations in MRI images.  Feature selection process might introduce bias and affect model performance.  The research paper didn't mention specific limitations or setbacks faced by the authors, so this is a general evaluation. |
| Brain tumour segmentation based on deep learning and an attention mechanism using MRI multi-modalities brain images | Ramin Ranjbarzadeh, Abbas Bagherian Kasgari, Saeid Jafarzadeh Ghoushchi, Shokofeh Anari, Maryam Naseri & Malika Bendechache | 2021 | Modalities: Developed a new brain tumour segmentation architecture leveraging the four MRI modalities.  Preprocessing: Preprocessing focuses on a limited area near the tumour for efficient feature extraction.  C-CNN: Utilizes a cascade CNN model to extract both local and global features effectively.  DWA: Implements a Distance-Wise Attention mechanism to enhance segmentation accuracy. | Improves efficiency by focusing on relevant image areas, reducing overfitting.  Enhances robustness to tumor size and location variations. | Complexity in the process of finding the tumor areas may require manual tuning.  Dependency on preprocessing steps for segmentation accuracy.  Limited effectiveness with tumor volumes larger than one-third of the brain. |
| NeuroNet19: an explainable deep neural network model for the classification of brain tumours using magnetic resonance imaging data | Rezuana Haque, Md Mehedi Hassan, Anupam Kumar Bairagi, Sheikh Mohammed Shariful Islam | 2024 | NeuroNet19 Architecture: Combines VGG19 and iPPM. VGG19 extracts features, and iPPM refines them for accurate classification.  Image Pre-processing: Includes Gaussian blur, Otsu’s thresholding, contour finding, image cropping, and power-law transformation for feature enhancement.  Dataset Splitting: Divides processed images into training, validation, and testing sets.  Data Augmentation: Augments the training set with operations like rotation, flipping, shear transformations, zooming, and shifting to increase diversity.  Model Training: Trains NeuroNet19 on the augmented training set and tunes hyperparameters using the validation set.  Model Evaluation: Evaluates NeuroNet19 using metrics like confusion matrix, classification report, accuracy score, precision, recall, F1-score, and CKC. | Enhanced Feature Extraction: Pre-processing techniques and iPPM refine features, improving classification accuracy.  Data Augmentation: Increases dataset diversity, improving model generalization.  Explainable AI: Uses LIME for transparency, providing insights into the model's decision-making. | Complexity: Implementation complexity due to multiple pre-processing steps and model architecture.  Data Augmentation Limitations: May not fully address challenges like imbalanced datasets or variability in tumor sizes and locations.  Generalizability: Performance on different datasets or real-world scenarios may vary, requiring further validation. |
| Deep neural network based artificial intelligence assisted diagnosis of bone scintigraphy for cancer bone metastasis | Zhen Zhao, Yong Pi, Lisha Jiang, Yongzhao Xiang, Jianan Wei, Pei Yang, Wenjie Zhang, Xiao Zhong, Ke Zhou, Yuhao Li, Lin Li, Zhang Yi and Huawei Cai | 2020 | Methods Collection, inclusion, and exclusion of patients. This study with retrospective information collection was approved by the Institutional Ethics Committee of West China Hospital in Sichuan University. We col lected 13,477 cases of BS images from patients suspected to have bone metastasis and underwent whole-body BS between January 1st, 2016, and June 30th, 2018. Then, cases with improper injection, improper imaging process, the patients who had definite primary bone tumor, and the ones did not undergo follow-up examinations were excluded. | AI model cost only 11.3 s to complete the interpretation of 400 cases, while three physicians spent 116, 140, and 153 min, respectively, to accomplish the same work, which is corresponding to a time savings of 99.88%. We collected 13 cases with correct interpretation by AI but misdiagnosed by all three physicians. Among these cases, 11 patients were found to have small lesions or insufficient resolution of radioactive uptake, were ignored or judged as benign by humans | However, in “real” clinical works, the patients’ medical records, such as injury history, surgical record, characteristics of other imaging modalities, and the results of laboratory tests, must be considered to obtain accurate BS interpretation. we hope the addition of fused reference CT and medical records would effectively reduce the diagnostic errors. Secondly, the unsatisfied capability in recognizing add-ons on patients, such as a catheter, is still a noticeable disadvantage of this AI model but easy for physicians |
| Artificial intelligence performance in detecting tumor metastasis from medical radiology imaging: A systematic review and meta-analysis | Qiuhan Zhenga , Le Yanga , Bin Zenga , Jiahao Lia, Kaixin Guoa , Yujie Lianga and Guiqing Liao | 2021 | AI model for the diagnosis of tumor metastasis (LNM and DM) from medical radiology imaging. We searched PubMed and Web of Science for studies published from January 1, 1997, to January 30, 2020, with no restrictions on regions, languages, or publi cation types.Three reviewers (QZ, LY and JL) extracted data independently using a predefined data extraction sheet, and uncertainties were resolved by another reviewer (BZ**).** which included true-positive (TP), false-positive (FP), true-negative (TN), and false negative (FN) results | the highest accuracy for different algorithms in these 34 studies with 48 tables, the pooled sensitivity was 87% (95% CI 84 89%), and the pooled specificity was 88% (84 92%), with AUC of 0.93(0.90 to 0.95) Of these 34 studies, 8 compared performance between AI algorithms and health-care professionals using the same sample, with 10 contingency tables for AI algorithm and 16 tables for health-care proffessionals. The pooled sensitivity was 89% (95% CI 83 93%) for AI algorithms and 72% (61 81%) for health-care professionals. | First, the design and practice of some included studies may make the research results out of clinical practice, lack of comparison with health-care professionals in diagnostic accuracy. Second, there were no prospective studies. All included studies were retrospective studies, selected from hospital medical records.Third, various indicators of diagnostic performance were used in the studies. The value of TP, TN, FP and FN at a specified threshold should at least be provided, but most studies did not give a threshold or explain the reason for choosing this threshold. |
| Microscopic brain tumor detection and classification using 3D CNN and feature selection architecture | A. Rehman, M. A. Khan, T. Saba, Z. Mehmood, U. Tariq, and N. Ayesha | 2021 | 3D Convolutional Neural Network (CNN): The authors likely use a 3D CNN to extract relevant features from microscopic brain tumor images. This type of network can process 3D data, like MRI scans, effectively capturing spatial relationships within the tumor region.  Feature Selection: After feature extraction, the authors might employ a feature selection technique to identify the most informative features for tumor classification. This helps reduce model complexity and potentially improve accuracy.  Classification: Finally, a machine learning model (e.g., neural network) classifies the tumor type based on the selected features. | Automated and objective: This approach aims to automate tumor detection and classification, reducing human subjectivity and error.  High accuracy: 3D CNNs have shown promising results in medical image analysis, potentially achieving high accuracy in tumor classification.  Focus on microscopic tumors: This method specifically targets microscopic tumors, which can be challenging to detect with traditional methods. | Data limitations: Access to high-quality, labeled microscopic tumor data might be limited, impacting model performance.  Interpretability: Deep learning models can be challenging to interpret, raising concerns about understanding their decision-making process.  Overfitting: Feature selection needs careful tuning to avoid overfitting the model to the training data, compromising generalizability. |
| Artificial Intelligence in Medical Imaging and Its Application in Sonography for the Management of Liver Tumor | Naoshi Nishida and Masatoshi Kudo | 2020 | Generally, three independent datasets are required for developing medical AI. A training set is required for the training of AI models, which contains many images to update model parameters. A tuning set is for the selection of a model’s hyperparameters that are necessary for the best expected output. A test set is for the final assessment of the performance of AI models. The splitting of curated data must be clean, and each dataset should be completely independent without any overlap with respect to lesions to avoid overfitting the output.CNNs are commonly applied for AI algorithm of imaging data. | The studies regarding the application of B-mode US images on machine learning for the diagnosis of liver tumor are summarized, where overall accuracy was 91.6 %; sensitivity of 90% for HCC and 93.3% for metastatic tumor were achieved .they examined the accuracy of two-class discriminations for cyst vs. hemangioma, cyst vs. malignant tumor, and hemangioma vs. malignant tumor, demonstrating the accuracy of more than 95% for each comparison.using artificial neural network show class discrimination for normal liver : accuracy of almost 90%, | On the other hand, because of the development of new treatments in HCC, management of this type of cancer is becoming complex . Recently, in addition to detection and diagnosis, AI model regarding the management of HCC, such as prediction of microvascular invasion, pathological grading, and treatment outcomes have been reported. Hu et al. proposed US-based radiomics score consisted of six selected features was an independent predictor of microvascular invasion in HCC which made an incorrect diagnosis for 14% |
| Deep learning for multigrade brain tumour classification in smart healthcare systems: A prospective survey | K. Muhammad, S. Khan, J. D. Ser, and V. H. C. D. Albuquerque | 2021 | multigrade classification:  The authors have analyze various deep learning architectures (e.g., convolutional neural networks), data preprocessing techniques, and evaluation metrics.  They might also discuss potential future directions and open challenges in this field. | Deep learning has shown promising results in various image classification tasks, potentially offering high accuracy in brain tumor classification.  Automation and reduced subjectivity compared to traditional methods.  Potential for integrating with smart healthcare systems for early diagnosis and personalized treatment. | Deep learning has shown promising results in various image classification tasks, potentially offering high accuracy in brain tumor classification.  Automation and reduced subjectivity compared to traditional methods.  Potential for integrating with smart healthcare systems for early diagnosis and personalized treatment. |
| Deep neural networks allow expert-level brain meningioma segmentation and present potential for improvement of clinical practice | Alessandro Boaro, Jakub R. Kaczmarzyk, Vasileios K. Kavouridis, Maya Harary, Marco Mammi, Hassan Dawood, Alice Shea, Elise Y. Cho, Parikshit Juvekar, Thomas Noh, Aakanksha Rana, Satrajit Ghosh & Omar Arnaout | 2021 | Dataset: A dataset of 10,099 healthy brain MRIs and 806 contrast-enhanced T1-weighted meningioma MRIs was used.  Algorithm Design: A three-dimensional convolutional neural network (3D-CNN) was trained on the healthy brain MRIs to segment entire brain volumes, and then fine-tuned using transfer learning on the meningioma MRIs for specific meningioma segmentation.  Performance Assessment: The algorithm's performance was evaluated using standard metrics for tumor segmentation performance, including Dice score and Hausdorff distance. Inter-expert variability was assessed by comparing the algorithm's results with those of human experts. | Accuracy: The final model achieved a median performance of 88.2%, reaching the spectrum of current inter-expert variability.  Efficiency: Automated segmentation saves time compared to manual techniques, which are often time-consuming and subject to inter-rater variability.  Clinical Impact: The algorithm has the potential to improve current clinical practice by providing accurate and efficient meningioma segmentation, which is critical for serial patient follow-up, surgical planning, and monitoring response to treatment. | Small Tumor Detection: The model missed two small tumors (volume < 1 cc), which could be a limitation in detecting very small tumors.  False Positives: The algorithm segmented 18 small vascular structures as tumours due to similarity in contrast uptake and rounded shape, indicating a potential for false positives in certain cases.  Clinical Integration: While the algorithm shows promise, further validation and integration into clinical workflows would be necessary to fully assess its impact and usability in real-world clinical scenarios. |
| Brain MRI image classification for cancer detection using deep wavelet autoencoder-based deep neural network | P. K. Mallick, S. H. Ryu, S. K. Satapathy, S. Mishra, G. N. Nguyen, and P. Tiwari | 2019 | Deep Wavelet Autoencoder (DWAE): This approach first employs a DWAE to extract features from brain MRI images. The DWAE combines the dimensionality reduction capability of autoencoders with the image decomposition properties of wavelet transforms.  Deep Neural Network (DNN): The extracted features are then fed into a DNN for classification of brain tumors as cancerous or non-cancerous. The DNN learns complex relationships between the features and the cancer presence. | Feature extraction: The DWAE is claimed to extract more informative features compared to traditional methods, potentially improving classification accuracy.  Data reduction: By reducing dimensionality, the DWAE can help manage computational costs and potentially improve model generalizability.  High accuracy: The study reports high accuracy in classifying brain tumors compared to other methods used at the time. | Limited data: The study uses a relatively small dataset, which might affect the generalizability of the model to other populations.  Black-box nature: DNNs can be challenging to interpret, making it difficult to understand how they arrive at their decisions.  Hyperparameter tuning: Tuning the DWAE and DNN parameters requires careful optimization, and the study might not have explored all possible configurations. |