## Deep Learning Product: AI-Powered Tumour Detection in Radiology

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### Objective of the Product

The goal of AI-powered tumour detection systems is to assist radiologists in accurately identifying and diagnosing tumours from medical imaging data such as MRI, CT scans, and X-rays. These systems aim to enhance diagnostic precision, reduce time-to-diagnosis, and improve patient outcomes by leveraging automated and consistent analysis.

### Solution Technology

Deep learning models, particularly CNNs, are employed to analyse medical images and detect tumours. These systems preprocess the imaging data to standardize input dimensions and remove noise, then use neural networks to extract relevant features and classify regions of interest. Advanced techniques like Transformers are now being integrated for better context awareness and interpretability in imaging sequences.

### Frameworks, Algorithms, and Tools

1. **Algorithms:**
   * CNNs for image feature extraction.
   * RNNs for temporal data analysis (e.g., tracking tumour progression over time).
   * Transformers for attention-based image analysis.
2. **Frameworks:** TensorFlow, PyTorch, and Keras are commonly used for training and deploying these models.
3. **Tools:** DICOM standard libraries for medical imaging data, OpenCV for preprocessing, and NVIDIA GPUs for accelerated computation.
4. **Dataset:** Open datasets like LUNA16 for lung cancer detection or TCGA for various types of tumour data are often used.

### Issues in the Current Solution

1. **Data Quality:** Medical imaging data may be noisy or incomplete, reducing model performance.
2. **Generalization:** Models trained on specific datasets might not generalize well to other patient populations or imaging devices.
3. **Interpretability:** Deep learning models often function as black boxes, making it difficult for clinicians to trust predictions without explanations.
4. **Regulatory Hurdles:** Approval for clinical use can be slow due to stringent healthcare regulations.

### Future Scope

1. **Federated Learning:** Distributed learning methods can enhance model training without compromising patient data privacy.
2. **Explainability Models:** Developing interpretable AI systems to boost clinician trust and adoption.
3. **Multi-modal Analysis:** Combining imaging data with patient records, genetic information, or lab results for comprehensive diagnostics.
4. **Real-Time Assistance:** Integrating AI systems directly into radiology workflows for real-time decision support.

Reference Papers  
  
***Enhancing Brain Tumour Detection: A Novel CNN Approach with Advanced Activation Functions***

* **Summary:** This study introduces an innovative approach to brain tumor detection by developing and implementing a novel Convolutional Neural Network (CNN) architecture enhanced with advanced activation functions. The aim is to support medical professionals by offering a more precise and automated tool for early diagnosis, which is essential for effective treatment planning.

*Access Link :* [PubMed Central](https://pmc.ncbi.nlm.nih.gov/articles/PMC11449684/?utm_source=chatgpt.com)

***Brain Tumour Detection and Classification in MRI Using Hybrid Vision Transformer and CNN***

* **Summary:** This research presents a framework that combines Vision Transformers (ViT) and Convolutional Neural Networks (CNN) to enhance the detection and classification of brain tumours in MRI scans. The hybrid model leverages the strengths of both architectures to improve accuracy in identifying tumour types.

*Access Link :* [Nature](https://www.nature.com/articles/s41598-024-71893-3?utm_source=chatgpt.com)

***CAFCT: Contextual and Attentional Feature Fusions of CNN and Transformer for Liver Tumour Segmentation***

* **Summary:** This paper proposes a hybrid model that integrates Convolutional Neural Networks (CNN) and Transformers for liver tumour segmentation in CT scans. The model incorporates modules like Attentional Feature Fusion (AFF) and Atrous Spatial Pyramid Pooling (ASPP) to enhance contextual information related to tumour boundaries, achieving superior performance compared to pure CNN or Transformer methods.

*Access Link :* [arXiv](https://arxiv.org/abs/2401.16886?utm_source=chatgpt.com)