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TUMOUR DETECTION MODEL USING CNN AND Grad-CAM

Ms. V. Sukanya, Asst. Prof
Sriharini Margapuri
Sree Varsha Lambadi
University College of Engineering, Osmania University

Abstract

Tumours are a major global health challenge, early detection of these tumours plays a huge role in improving survival rates. Magnetic Resonance Imaging (MRI) is commonly used for diagnosis of tumours by medical professionals. Deep learning, particularly CNNs, has shown promise in automating tumor detection with high .accuracy

This research aims to develop a CNN-based system capable of detecting tumours in various parts of the body - organs like brain, lung, breast and kidney. GradCAM and Contour Mapping are employed to visualise and highlight the predicted area. Additionally, the system is deployed on Streamlit to provide a user-friendly interface for real-time clinical use

Introduction .1

Cancer and its Impact 1.1

Cancer remains as one of the foremost global health challenges, responsible for nearly 10 million deaths annually approximately one in every six deaths worldwide. Amongst these, lung, breast and colon cancer are the most –[4] prevalent, accounting for an estimated 2 million cases for each type. Alarmingly, lung cancer alone leads to an approximate 1.80 million deaths per annum with colon cancer and breast cancer leading to 916 000 and 685 000 .deaths per annum

The prognosis for cancer patients significantly improves with early detection. This includes not only diagnosing tumors at their initial stages but also implementing effective screening to identify precancerous tumors before symptoms arise. Early intervention is strongly correlated with increased treatment success rates and improved .patient survival outcomes

Magnetic Resonance Imagining (MRI) in Cancer Detection 1.2

Magnetic Resonance Imaging (MRI) has become a cornerstone in the clinical detection and evaluation of tumors due to its high-resolution, non-invasive imaging capabilities [1]. MRI scanners utilize strong magnetic fields and radio waves to detect signals from hydrogen atoms within the body, allowing for detailed cross-sectional images of internal organs. These images are used by medical professionals in identifying abnormalities and .distinguishing between benign and malignant tumors

Deep Learning in the Medical Industry 1.3

In recent years, deep learning (DL) has emerged as a transformative technology in the medical imaging domain Convolutional Neural Networks (CNNs), in particular, have demonstrated exceptional performance in image .[9] classification, segmentation, and anomaly detection tasks. In the medical field, DL models are increasingly being used to support clinical decision-making, reduce diagnostic errors, and automate time-consuming processes. From identifying diabetic retinopathy in fundus images to segmenting lesions in brain MRIs, deep learning offers a powerful, scalable approach for enhancing diagnostic accuracy and efficiency across a range of applications .[7]

In this study, we propose a Convolutional Neural Network (CNN)-based framework for automated tumor detection across MRI scans of multiple organ systems. To enhance the interpretability of our model's predictions, we integrate Gradient-weighted Class Activation Mapping (Grad-CAM) and contour mapping techniques, providing visual insights into the model's decision-making process. Furthermore, we implement the system using Streamlit to create an intuitive, real-time interface suitable for clinical environments. Our approach aims to assist medical professionals in achieving faster, more accurate diagnoses, ultimately contributing to improved patient .care and outcomes

Literature Survey .2

M. Musthafa et al., "Enhancing brain tumor detection in MRI images through explainable AI using 2.1 Grad-CAM with ResNet50," BMC Medical Imaging, vol. 24, Article 107, May 2024.]8[

Objective 2.1.1

The objective of the study by M. Musthafa et al., published in BMC Medical Imaging (2024), was to develop a deep learning model aimed at enhancing brain tumor detection in MRI images. The study sought not only to achieve high classification performance but also to incorporate explainability into the model to aid clinical .decision-making

Methodology 2.1.2

The researchers utilized the ResNet50 convolutional neural network (CNN) architecture to perform the classification tasks on brain MRI images. To provide visual interpretability and build clinical trust, they integrated Gradient-weighted Class Activation Mapping (Grad-CAM) into the model pipeline. Grad-CAM was employed to generate heatmaps highlighting tumor regions associated with the model's predictions. Additionally, data augmentation techniques were applied to the training set in order to increase model generalizability and .mitigate overfitting, thereby enhancing the robustness of the results

Results 2.1.3

The developed model demonstrated outstanding performance, achieving a testing accuracy of 98.52%. Furthermore, precision and recall metrics both exceeded 98%, suggesting a high level of reliability and effectiveness in detecting brain tumors. The Grad-CAM visualizations effectively highlighted the tumor regions .within MRI images, providing intuitive and clinically relevant insights into the model's decision-making process

Limitations 2.1.4

Despite its strong performance, the study had notable limitations. The dataset used was restricted exclusively to brain MRI images, and therefore, the model's applicability to detecting tumors in other organs remains untested. Additionally, the dataset was relatively small and less diverse, which may limit the model's exposure to a broader range of anatomical and pathological variations, potentially affecting its generalizability to unseen clinical .scenarios

Ali, S., Li, J., Pei, Y., Khurram, R., Rehman, K. U., & Rasool, A. B. (2021). State-of-the-Art 2.2 Challenges and Perspectives in Multi-Organ Cancer Diagnosis via Deep Learning-Based Methods. Cancers, 13(21), 5546.]6[

Objective 2.2.1

The objective of this study is to provide a comprehensive review of current deep learning methodologies applied to multi-organ cancer diagnosis. The review aims to highlight existing challenges within the field and propose .future directions for improvement, with a focus on enhancing model performance and clinical applicability

Methodology 2.2.2

An extensive literature review was conducted, examining deep learning techniques utilized in the diagnosis of cancer across various organs. The study analyzed the performance, advantages, and limitations of different convolutional neural network (CNN) architectures as applied to medical imaging. Additionally, the integration of explainable AI (XAI) methods, such as Gradient-weighted Class Activation Mapping (Grad-CAM), was discussed to evaluate how these approaches enhance the interpretability of deep learning models and support .clinical decision-making

Results 2.2.3

The review found that while deep learning models have achieved high accuracy in cancer detection tasks, their inherent "black-box" nature continues to pose significant challenges for widespread clinical adoption. Techniques like Grad-CAM have proven effective in offering visual explanations for model predictions, thereby increasing trust among healthcare professionals. The findings emphasize the importance of developing models that not only maintain high accuracy but also provide transparent and interpretable outputs to better support .decision-making in medical diagnostics

Limitations 2.2.4

Several limitations were identified through the review. A major challenge is the scarcity of large, annotated datasets for certain types of cancer, which hampers the development, training, and validation of robust deep learning models. Furthermore, it was noted that most existing studies focus primarily on single-organ cancer detection, indicating a critical gap in multi-organ diagnostic approaches. Finally, the lack of standardized evaluation metrics across different studies complicates the direct comparison of model performances, presenting .another hurdle for advancing the field

Challenges of the Literature Survey 2.3

Data Issues 2.3.1

A major challenge in applying deep learning to cancer diagnosis is the limited availability of large, well-balanced datasets. Many studies rely on small, often imbalanced datasets, which can bias model performance and reduce generalizability. Additionally, there is significant variability in imaging protocols and equipment across different institutions, leading to cross-institution image heterogeneity. This variability complicates model training and .reduces the ability to generalize findings across diverse clinical settings

Model Interpretability 2.3.2

The lack of transparency in deep learning models remains a critical barrier to clinical adoption. These models often function as "black boxes," making it difficult for healthcare professionals to trust and validate their outputs. Explainable AI (XAI) techniques, particularly Gradient-weighted Class Activation Mapping (Grad-CAM), have been instrumental in addressing this challenge by providing visual explanations and accurate tumor contouring. Nevertheless, further improvements are needed to enhance the clinical interpretability and actionable insights .derived from these models

Generalization .2.3.3

Current deep learning models often struggle with poor cross-organ performance, highlighting difficulties in adapting models trained on one organ system to others. Additionally, the development of models capable of multi-organ tumor detection remains a significant challenge. Differences in tumor appearance, size, and location across organs demand models that are highly adaptable and capable of learning diverse pathological features without .compromising accuracy

Computational Demands 2.3.4

Training deep learning models for medical imaging applications requires substantial computational resources. High memory demands, long training times, and the need for specialized hardware, such as GPUs or TPUs, present practical challenges for many institutions. These computational demands can limit access to advanced .AI technologies, particularly in resource-constrained healthcare settings

Objectives .3

1. To build a model that accurately identifies the organ in the MRI: The model is expected to discern the .differences between organs and how tumours differ from organ to organ
2. The model should be able to correctly discern whether a tumour is present or not: After understanding .the type of organ being examined, the model should be able to detect whether tumours and/or cancers are present
3. To localise the tumour accurately: If a tumour is detected, the model should then mark the location of the .tumour in the organ present and should give a visual representation of the tumorous region

:The following paper shows the contributed research of the following

1. Methodology
2. Results
3. Conclusion

Methodology .4

Data Collection and Preprocessing 4.1

The dataset used in this study was compiled from publicly available medical imaging resources and includes MRI scans of various human organs such as the brain, lungs, breast, and kidneys. To create an unbiased environment, both tumorous and healthy organ images were incorporated, with the healthy images serving as a control study. To ensure uniformity and improve computational efficiency, all images were resized to 128×128 pixels. They were also converted to greyscale to reduce input complexity without compromising diagnostic features. Normalization was applied to scale pixel intensity values to alter the range from 0-255 to be in between and 1.0. Additionally, a channel dimension was added to each image to meet the input requirements of 0.0 convolutional neural networks (CNNs). Each image in the dataset was given a label between 0 to 7 depending .on the organ type and presence of a tumor. Code snippet 4.1 shows the classes created

```
Code 4.1: Class Labels

,'class_labels = {0: 'Brain Tumor', 1: 'Brain No Tumor', 2: 'Breast Tumor', 3: 'Breast No Tumor
{'Kidney Tumor', 5: 'Kidney No Tumor', 6: 'Lung Tumor', 7: 'Lung No Tumor' :4
```

Model Building 4.2

A custom CNN architecture was designed to automatically extract the features from the preprocessed MRI scans. The model is a Sequential model that consists of three convolutional layers, each followed by a Rectified Linear Unit (ReLU) activation function to introduce non-linearity, and three max-pooling layers to reduce spatial dimensions while preserving important features. Following the convolutional blocks, a flatten layer was used to convert the two-dimensional feature maps into a one-dimensional feature vector, which was then passed through two fully connected dense layers. The final dense layer uses a softmax activation function to output a probability .distribution across the possible categories, corresponding to different tumour types or healthy tissues

.Code snippet 4.2 shows the custom model that was built

```
Code 4.2: Model

])model = Sequential
,Conv2D(32, (3, 3), activation='relu', input_shape=(128, 128, 1))
,MaxPooling2D))2, 2((
,Conv2D(64, (3, 3), activation='relu')
,MaxPooling2D))2, 2((
,Conv2D(128, (3, 3), activation='relu')
,MaxPooling2D))2, 2((
,()Flatten
,Dense(128, activation='relu')
Dense(len(class_labels), activation='softmax')  # Multi-class output
([
```

.Figure 4.1 shows the detailed summary of the CNN model that was built

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 126, 126, 32)	320
max_pooling2d (MaxPooling2D)	(None, 63, 63, 32)	0
conv2d_1 (Conv2D)	(None, 61, 61, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 30, 30, 64)	0
conv2d_2 (Conv2D)	(None, 28, 28, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 14, 14, 128)	0
flatten (Flatten)	(None, 25088)	0
dense (Dense)	(None, 128)	3,211,392
dense_1 (Dense)	(None, 8)	1,032

Total params: 3,305,098 (12.61 MB)
Trainable params: 3,305,096 (12.61 MB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 2 (12.00 B)

Figure 4.1 CNN Model Summary

Figure 4.2 gives a flowchart of the image input in the custom CNN Model. The flowchart depicts the feature extraction done to the MRI scan as it is being analyzed by the model. The starting image is a 128 x 128 image

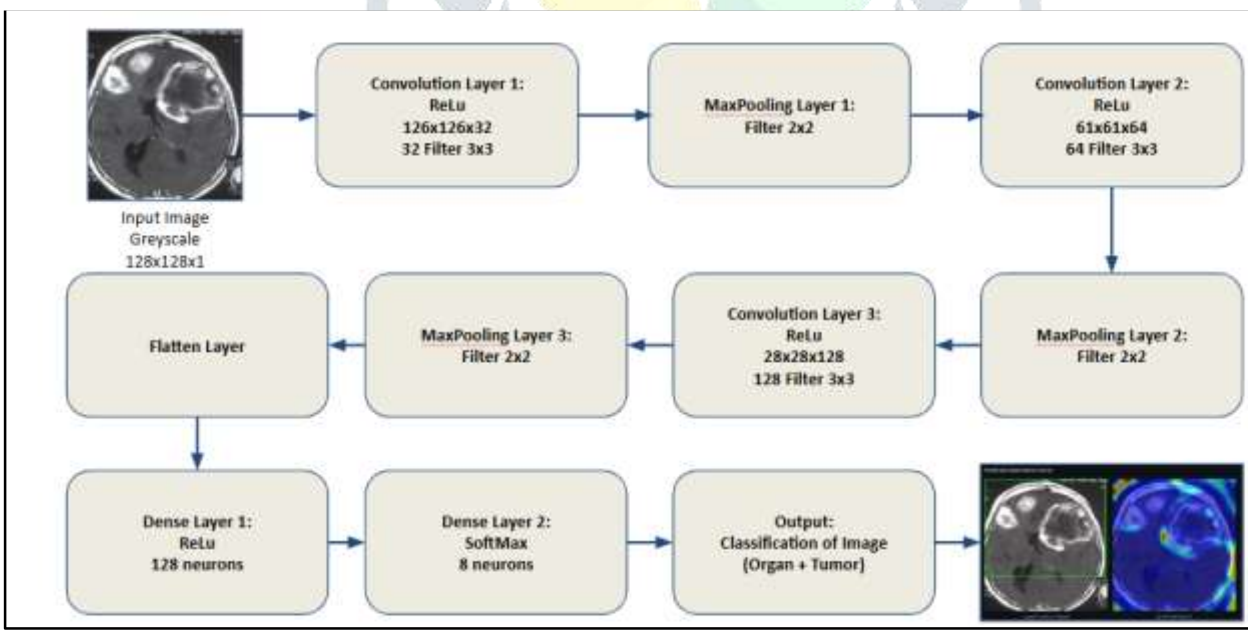

Figure 4.2 Architecture Flowchart

Training and Evaluation 4.3

The training process utilized the Adam optimization algorithm, chosen for its adaptive learning capabilities and computational efficiency. To handle the multiclass classification task, Sparse Categorical Cross-Entropy was used as the loss function. The dataset was divided into training and testing sets in an 80:20 ratio, and training was conducted using a batch size of 32 over 10 epochs. Throughout the training process, various hyperparameters and layer configurations were iteratively refined to maximize accuracy while avoiding overfitting or underfitting. Upon completion of training, the model achieved a validation accuracy of 93.26% and a corresponding loss of .0.2237

Localisation of the Tumour 4.4

To provide visual insights into the model's decision-making process, Gradient-weighted Class Activation Mapping (Grad-CAM) was employed. This technique generates a heatmap that highlights regions of the input image that were most important to the model in making its prediction. Grad-CAM operates by computing the gradient of the predicted class score with respect to the activations of the final convolutional layer. These .gradients are then used to weight the feature maps, which are subsequently combined to produce a visual heatmap

To provide another viewpoint on tumour localization, image contouring was also employed. This technique enhances interpretability by detecting and outlining the boundaries of abnormal regions within the MRI scans. Image contouring operates by identifying the edges and shapes of objects present in the image, effectively isolating distinct structures. By comparing this method to the Grad-CAM output, it becomes possible to delineate .the tumour regions more precisely

Deployment with Streamlit 4.5

For practical deployment, the trained model was integrated into a user-friendly web application using the Streamlit framework. This interface enables users to upload MRI scans and receive immediate classification results, accompanied by Grad-CAM-generated heatmaps and contour overlays. The application facilitates real-.time, interpretable diagnostics, making it accessible for clinical use and further research

Results .5

Predictions 5.1

To test the results of our model, Figure 5.1 demonstrates the inputted image given to the model for prediction. .The image shows the MRI cross-section of the brain containing a tumor

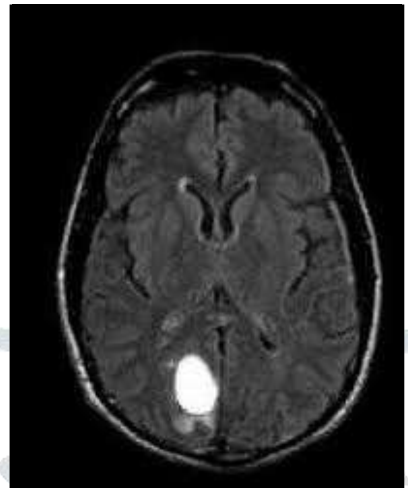

Figure 5.1 Test MRI Scan of Brain

.When given to the model, the following output (as given in Figure 5.2) is shown

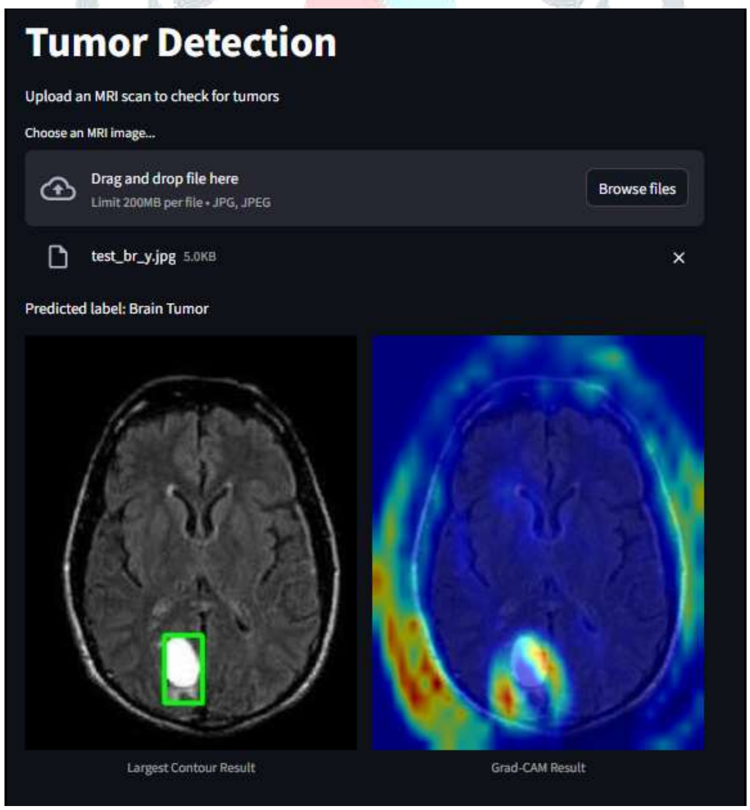

Figure 5.2 Model Predictions and Visualization

As above, the model is able to accurately predict the organ and the presence of the tumor. Likewise the Image contouring image (left) highlights the tumor location by drawing a green boundary box. The Grad-CAM results .create a heatmap where areas closer to the tumor are more warm than healthy tissue of the given MRI scan

Model Accuracy 5.2

Figure 5.3 depicts the accuracy of the model in prediction of each of the 4 organs and its presence of the tumor. Brain, Kidney and Breast tumors gave an accuracy of above 90% where lung tumors gave an accurate prediction .closer to 87%

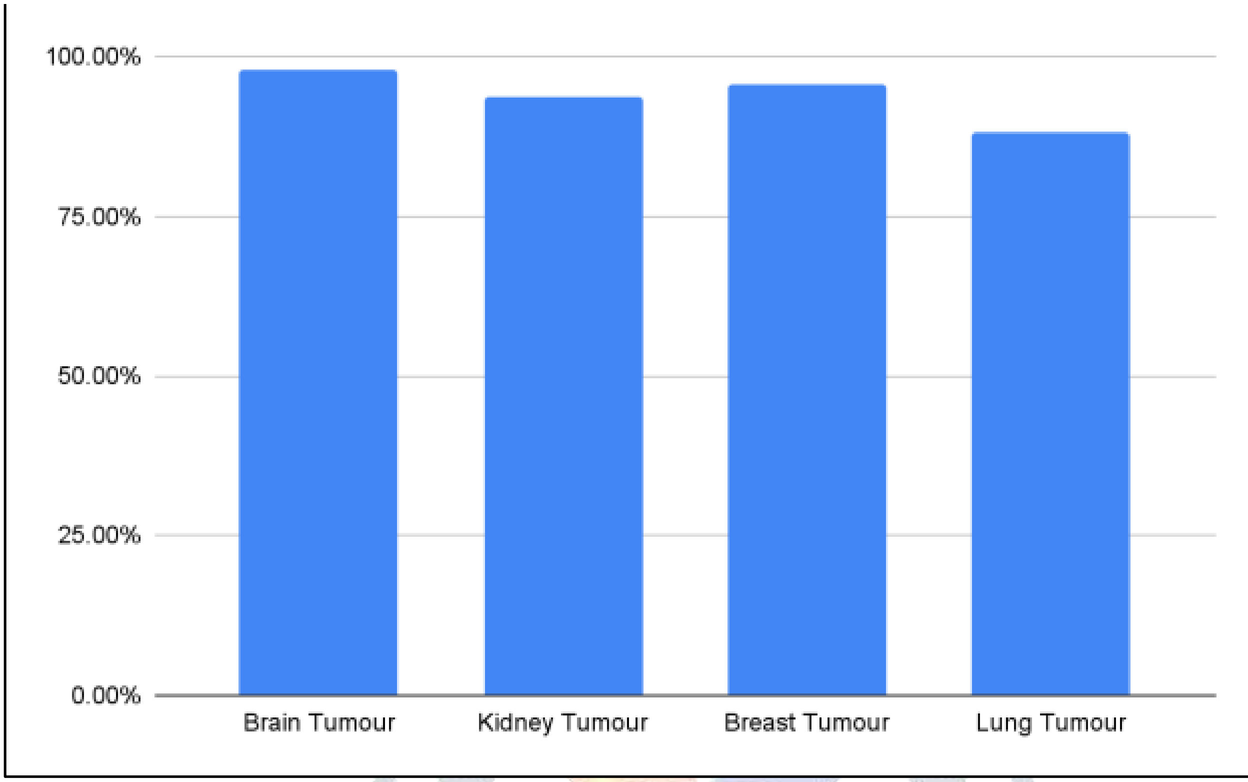

Figure 5.3
Accuracy of Predictions

Final Results 5.3

The proposed convolutional neural network model demonstrated high classification accuracy across all organ types included in the dataset, indicating its effectiveness in distinguishing between healthy and tumorous MRI scans. The integration of Grad-CAM visualizations provided valuable insights into the model's decision-making process by consistently highlighting regions of the images that corresponded to tumour presence. These heatmaps facilitated interpretability and added a layer of transparency to the classification outcomes. Furthermore, the application of image contouring techniques enhanced the localization of abnormalities by clearly outlining tumour boundaries, thereby improving the clarity and clinical utility of the visual output. Finally, deployment through the Streamlit interface proved to be both efficient and user-friendly, enabling real-time analysis and .making the diagnostic tool accessible to both medical professionals and researchers

Conclusion .6

Conclusion 6.1

This study introduces a deep learning model for the detection and localization of tumours across multiple organs using MRI imaging. By leveraging a custom-designed convolutional neural network, the system achieves high classification accuracy while maintaining generalizability across different organ types. The incorporation of interpretability techniques, such as Gradient-weighted Class Activation Mapping (Grad-CAM) and image contouring, significantly enhances the transparency of the model's decision-making process. These visual tools not only provide valuable insights into the regions of interest within the scans but also increase the system's .trustworthiness in clinical environments

Deployment through a Streamlit-based interface further improves the system's practicality by enabling real-time, user-friendly interaction. This interface allows clinicians and researchers to upload MRI scans, receive diagnostic .predictions, and visualize tumour localization instantly, thereby facilitating informed clinical decision-making

Future Scope 6.2

While the current model demonstrates strong performance, several avenues for future work remain. Incorporating a larger and more diverse dataset—including varying imaging modalities such as CT and PET—could further enhance the model's generalizability and diagnostic power. Additionally, integrating three-dimensional (3D) CNNs could enable volumetric analysis of MRI scans, potentially improving the accuracy of .tumour boundary detection and classification

Future iterations of the system could also benefit from incorporating clinical metadata (e.g., patient history, age, or genetic markers) to support multimodal learning. Moreover, the implementation of active learning and semi-.supervised techniques could allow the model to improve over time with minimal human annotation

Finally, a comprehensive validation phase involving collaboration with medical professionals and real-world clinical trials is essential before large-scale deployment. This would help assess the model's performance under real diagnostic conditions and identify any critical limitations or biases, ultimately paving the way toward .regulatory approval and integration into clinical workflows

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