**Table 6:** **Comparison of various Classification Models**

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| **Reference** | **Technique** | **XAI** | **Advantage** | **Disadvantage** | **Performance** |
| Yan *et al.* [94] (2023) | Explainable brain tumor detection system | Grad-Cam++ | Benefit of post-hoc explainability was integrated into the categorization model | Maybe computationally demanding. | Accuracy: 95.46% |
| Aly *et al.* [95] (2024) | ViT-GRU | LIME and SHAP | Excellent results on all important metrics | Longer training periods | F1-score: 98.5%, precision: 98.8% and recall: 98.8% |
| Haque *et al.* [96] (2024) | NeuroNet19 | LIME | High precision with multi-scale feature extraction | Absence of precise information on computational efficiency | Cohen Kappa, F1: 99.2%, Accuracy: 99.3%, Precision: 99% and Recall: 99% |
| Mahesh *et al.* [97] (2024) | ResNet50 with Grad-CAM | Grad-CAM | Excellent explainability and transparency | Potentially less effective for large data sets | Precision: 98%, Recall: 98%, Accuracy: 98.52% |
| Hosny *et al.* [98] (2025) | Ensemble deep learning model | Grad-CAM | Combines the strengths of many pre-trained models. | The complexity of the ensemble might contribute to lengthier training times. | Accuracy: 99.02%, precision: 98.75%, recall: 98.98% and F1: 98.86%. |
| Mzoughi *et al.* [99] (2024) | ViT | SHAP, LIME and Grad-CAM | Outperforms CNN models and XAI approaches for interpretability. | May need enormous computing resources. | Accuracy: 91.61% |
| Ahmed *et al.* [100] (2023) | VGG16 | Layer-wise Relevance Propagation | Simple and efficient binary categorization. | Complex tasks may not be easily generalized. | Accuracy: 97.33% |
| Chitnis *et al.* [101] (2022) | LeaSE | Learning-by-Self-Explanation | Automatically search for high-performance neural networks. | Might not be as effective as networks that are manually created. | AUC: 95.6%, accuracy: 90.6% |
| Ariful Islam *et al.* [102] (2025) | Improved CNN based DenseNet121 | Grad-CAM++ | High precision and efficacy when integrating Explainable AI | Possible overfitting in the absence of appropriate data augmentation | Accuracy: 98.4% |
| Ingh *et al.* [103] (2025) | DenseNet-169 | SHAP and Grad-CAM | Model size reduction with excellent precision | Some accuracy may be lost as a result of model compression. | Accuracy: 97.07% |

**Table 5:** **Comparison of various Segmentation Models**

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| --- | --- | --- | --- | --- | --- |
| **Author** | **Technique** | **XAI availability** | **Advantage** | **Disadvantage** | **Performance (%)** |
| Sajid et al. [84] (2019) | Hybrid CNN | N/A | Overfitting, unbalance and high dice scores were addressed | Dataset older (BraTS 2013) | 86% sensitivity, 86% specificity and 91% dice coefficient |
| Akil et al. [85] (2020) | Attention based Deep CNN | N/A | Strong segmentation on BRATS 2018 | No XAI/interpretability | Dice score of 90% |
| Vu et al. [86] (2020) | SE Blocks Cascaded Ensemble U-Net strategy | N/A | Modular design, ensemble strategy | Accuracy of the enhanced region is slightly reduced | 88.06% of dice coefficient |
| Ranjbarzadeh et al. [87] (2021) | CNN-based approach | N/A | High precision and less superfluous details | Intricate design | 92% of dice coefficient |
| Havaei et al. [88] (2017) | Cascaded CNN model | N/A | Captures background and addresses imbalance | Reducing the accuracy | 85% of dice coefficient |
| Dushyantha et al. [89] (2025) | FL based CNN model | Yes | High precision, confidentiality and interpretability | Heavy on infrastructure | 96.8% Accuracy, 96.6% F1- score |
| Ullah et al. [90] (2024) | DeepLabv3 based IRB models | Yes | Interpretable, optimized and modular | Implementation is Complex | Accuracy of 92.68% |
| Hasan et al. [91] (2023) | Multi CNN approach | Yes | Compared many models, interpretable | ResNet only slightly better than others | 96% of Accuracy, Dice ~85% |
| Xie et al. [92] (2024) | Counterfactual Gen. + Topological XAI | Yes | Unsupervised, explainable | Lower IoU/Dice compared to supervised | 75.85% Dice, 63.73% IoU |
| Tiwary et al. [93] (2025) | EfficientNet-UNet | N/A | Excellent feature use and high accuracy | Loss might be further enhanced | 99.25% Accuracy, Loss 0.2991 |
| Li et al. (2024) [104] | Importance-aware 3D visualization | Visualization (3D PET–CT CBIR) | Highlighted diagnostically significant regions via optimized rendering | Requires multimodal data integration | Improved interpretability & retrieval efficiency |
| Guerroudji et al. (2024) [105] | AR-based 3D brain tumor segmentation | AR Visualization | Combined contour modeling and 3D Slicer reconstruction | Dataset limited to one center | Accuracy: 98.61% |
| Wang et al. (2021) [106] | ECSU-Net | 2D–3D Hybrid Visualization | Embedded clustering and adaptive fusion for efficient segmentation | Task-specific tuning needed | Dice: 95.6%, Accuracy: 96.2% |
| Zhao et al. (2021) [107] | Modified GAN-cAED | Controlled Segmentation | Synthetic PET-CT + CTA fusion to prevent vessel damage | Focused on liver imaging only | Improved vessel segmentation accuracy |
| Kumar et al. (2020) [108] | SPST-CNN | Spatial Pyramid Visualization | Scale-invariant tagging of intraoperative liver views | Limited to intraoperative settings | mAP: 85.9% |