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Serunet (Smart Explainable Platform for Radiological Understanding): A Unified Multi-Modal AI System for Neurological Disorder Detection

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Abstract

Neurological diseases affect over one billion people globally, yet countless communities still lack basic access to specialist care, especially during emergencies. This work presents the first unified artificial intelligence platform capable of detecting and analyzing four major neurological conditions (brain tumors, strokes, Alzheimer's disease, and multiple sclerosis) within a single, web-accessible system. SeruNet platform addresses critical gaps in neurological care delivery by integrating condition-specific expert systems with advanced explainable AI techniques including one of the first documented application of XRAI (eXplanation with Region Attribution Integration) for neurological imaging. The unified architecture combines 2D and 3D analysis capabilities across multiple imaging modalities while maintaining specialized accuracy for each neurological condition. Key innovations include region-based attribution that aligns with clinical reasoning, a novel two-stage multiple sclerosis risk prediction model, and comprehensive bias-aware monitoring systems. Web-based deployment eliminates infrastructure barriers, enabling immediate access through standard browsers without specialized hardware requirements. This unified approach represents a paradigm shift from fragmented, condition-specific AI systems toward integrated, accessible neurological diagnostics designed for global health equity and immediate clinical deployment.

Keywords: SeruNet, XRAI, Neurological imaging, Multiple imaging modalities, Region-based attribution, Web-based deployment.

1. INTRODUCTION

SeruNet (Smart Explainable Platform for Radiological Understanding) is a unified multi-modal and explainable web-based intelligence platform capable of detecting and diagnosing brain tumors and strokes and predicting Alzheimer's disease and multiple sclerosis from an integrated platform.

1.1. Brain Tumor Detection and Classification

Brain tumor diagnosis [1] represents one of the most challenging medical conditions due to non-specific symptomatology and highly variable radiological features in MRI scans, making accurate interpretation extremely difficult even for experienced radiologists in high-pressure clinical environments [2,3]. The intricate process of MRI scan interpretation is time consuming, requiring specialized expertise and being

prone to human error, particularly when handling tumor heterogeneity and challenging anatomical structures [4].

Current deep learning approaches utilizing Convolutional Neural Networks (CNNs) have emerged as the most promising solution in neuroimaging, with architectural frameworks based on U-Net, DeepLabV3+, EfficientNet, and ResNet50 demonstrating state-of-the-art performance on benchmark datasets including BraTS and TCIA [5–10]. However, these high-performance models typically operate as "black boxes," providing predictions without explanations regarding their decision-making processes, creating serious drawbacks in clinical applications where accountability and interpretability are paramount [11,12].

The lack of transparency has contributed to increasing interest in Explainable Artificial Intelligence (XAI) development [13]. NeuroXAI accommodates various backpropagation-based XAI methods and provides 2D and 3D visualizations specifically designed for classification and segmentation tasks [11]. The Neuro-XAI pipeline integrates DeepLabV3+ with Bayesian hyperparameter optimization and entropy-based uncertainty estimation to generate reliable and interpretable results [12]. The integration of EfficientNetB0 with Grad-CAM achieved over 98% classification accuracy while producing interpretable visual diagnostic saliency maps consistent with clinical expectations [9].

XAI techniques including Grad-CAM, SHAP, LIME, SmoothGrad, and Integrated Gradients generate visualizations in heatmaps and attribution maps that accurately locate input image areas contributing significantly to model decisions [4]. These visual representations verify that models concentrate on clinically relevant areas such as enhancing tumor edges rather than tissues with no clinical significance [9]. Regulatory demands such as the EU's GDPR now require interpretability of algorithms in clinical decision-making systems [14,15].

1.2. Stroke Detection and Risk Prediction

Stroke represents the second leading cause of death globally and the third principal cause of disability worldwide [16–18]. The Hemorrhage Evaluation and Detector System for Underserved Populations (HEADS-UP) achieved 95.80% average precision, 91.40% precision, and 91.40% recall for intracranial hemorrhage detection using Google Cloud Vertex AutoML with 752,803 labeled images, specifically designed for resource-poor healthcare settings [19].

Advanced hybrid architecture has demonstrated remarkable performance. The ViT-LSTM model combining Vision Transformer and Long Short-Term Memory networks achieved 94.55% accuracy on the BrSCTHD-2023 dataset from Rajshahi Medical College Hospital and 96.61% on the Kaggle brain stroke dataset [20]. This method incorporated explainable AI methods including attention maps, SHAP, and LIME to promote clinical interpretability. Compact CNN models achieved 97.2% validation accuracy with 20.1 million parameters and 76.79 MB memory footprint, representing a 25% parameter and 76% memory decrease compared to state-of-the-art solutions [21].

The clinical importance of rapid stroke identification becomes apparent considering that ischemic strokes comprise 85% of all cases, with current field triage stroke scales exhibiting false-positive rates of 50-65% and peak accuracy of only 79% with NIHSS scores of 11 or more [22]. Portable diagnostic technologies demonstrate potential solutions: the Strokefinder MD100 achieves 100% sensitivity and 75% specificity for intracranial hemorrhage detection within 45 seconds [22].

Interpretable machine learning models achieved 92.0% accuracy for cognitive disorder classification using Random Forest with fusion features and 82.5% accuracy for motor disorder classification using Linear Discriminant Analysis [23]. EfficientNetB0 for brain stroke classification achieved 97% classification accuracy, 96% precision, 97% recall, and 97% F1-score [24]. Automatic deep learning

systems for malignant cerebral edema prediction achieved 100% recall and 87% precision using Long Short-Term Memory neural networks [25].

For stroke risk prediction, studies utilizing datasets with 5,110 patient records demonstrated that Random Forest achieved the highest accuracy of 97% after preprocessing including SMOTE-based class balancing [26,27]. Stacking algorithms achieved 98.9% AUC, 98% accuracy, and 97.4% recall, precision, and F-measure [28]. Transfer learning methods using VGGFace models achieved 97% accuracy in classifying healthy versus sick individuals [29]. Comprehensive saliency technique comparisons indicated that ScoreCAM, XRAI, GradCAM, and GradCAM++ consistently yielded focused and clinically meaningful attribution maps [30].

1.3. Alzheimer's Disease Assessment and Detection

Alzheimer's disease affects approximately 55 million individuals globally, with projections doubling by 2050, representing the most prevalent form of dementia characterized by amyloid plaques and neurofibrillary tangles [31,32]. The disease progresses through distinct stages from cognitively normal aging through mild cognitive impairment to full AD dementia, with 10-15% of MCI patients progressing to AD annually [33].

Machine learning approaches have transitioned from traditional techniques like Support Vector Machines, Random Forest, and logistic regression to sophisticated deep learning frameworks [34]. CNNs have emerged as the de facto architecture, with studies reporting that MobileNetV3 achieved 93% accuracy and DenseNet121 reached 88% accuracy for AD classification [35]. Advanced architectures like 3D Hybrid Compact Convolutional Transformers integrate local CNN feature extraction with global transformer attention mechanisms, achieving 96.06% accuracy for multi-class classification [36].

Multimodal approaches combining T2-weighted MRI with DTI using YOLOv11 architecture achieved 93.6% sensitivity, 91.6% recall, and 96.7% mAP50 for simultaneous structural and microstructural brain analysis [31]. Ensemble methods demonstrated increased diagnostic accuracy by combining various models to capitalize on complementarities and reduce individual model biases [35].

Explainable AI development has attempted to address clinical interpretability challenges. Grad-CAM utilizes gradient information for spatial region identification, SHAP provides quantitative values for each input component based on game theory reasoning, and LIME generates explanations through interpretable surrogate models [37]. Layer-wise Relevance Propagation (LRP) operates through backpropagating relevance scores layer by layer, while XRAI represents a considerable improvement over pixel-level attribution techniques by adopting region-based methodology that over-segments images into coherent anatomical regions, XRAI's application to medical imaging, particularly neurological disorders detection, remains unexplored in published literature, with existing medical AI research predominantly relying on Grad-CAM, LIME, and SHAP approaches [38].

Critical limitations persist in current XAI approaches, including low specificity with many methods producing explanations highlighting anatomically irrelevant regions, absence of standard evaluation metrics, and minimal deployment in clinical practice due to black-box mechanisms. Current explainability approaches typically do not achieve the degree of clinical interpretability necessary for real-world deployment, with classical gradient-based approaches commonly identifying anatomically irrelevant areas or generating inconsistent explanations [39].

1.4. Multiple Sclerosis Prediction and Risk Assessment

Multiple sclerosis research has focused on predicting conversion from clinically isolated syndrome to clinically definite multiple sclerosis using machine learning approaches. Studies investigating 84 CIS

patients, extracting over 120 lesion-shape and intensity features from 3D FLAIR and T1-weighted MRI scans, achieved 84.5% accuracy using random forest classification, significantly outperforming conventional dissemination-in-space criteria [40]. Combined lesion-load metrics with demographic and clinical variables in 112 CIS patients demonstrated improved discrimination (AUC = 0.82) using support vector machines with radial basis function kernels, although interpretability was limited to global feature-importance weights [30].

Enriched MRI data with metabolic information from MR spectroscopy in 96 CIS patients achieved AUC of 0.88 using logistic regression incorporating volumetric lesion measures and spectroscopy features, though requiring specialized acquisition protocols [41]. Linear SVM on 68 CIS patients using handcrafted descriptors of lesion shape and spatial distribution achieved 78% accuracy while underscoring the value of spatial lesion topology [42].

Deep learning methods have shown exceptional promise. Multi-center cohorts of 212 CIS patients across three North American hospitals, combining CNN features with 25 clinical variables, achieved AUC of 0.91, yet interpretability was limited to post-hoc saliency maps offering only coarse localization without quantifying individual feature contributions [43]. Evaluation of five supervised classifiers on 411 CIS patients from dual sites showed Random Forest attaining perfect F1-score on the Mexican subset (n=273), though model transparency was limited to permutation-importance rankings [44].

Random Forest applied to 265 Mexican-mestizo CIS patients yielded AUC of 0.93 and 87% accuracy using Recursive Feature Elimination to reduce 40 variables to 12 primarily imaging and immunological markers, yet threshold calibration and formal explainability beyond global feature rankings were not addressed [45].

2. Methodology

2.1. Overall System Architecture and Design Philosophy

SeruNet platform is developed as a four-module diagnostic structure, with each module contributing complementarily and integrated through a web-based explainable AI interface. The system architecture addresses existing gaps in neurological AI systems by offering a unified SeruNet platform that can identify brain tumors, classify strokes with risk prediction, diagnose Alzheimer's disease with bias monitoring, and estimate multiple sclerosis risk, all within a single, accessible system. The design philosophy emphasizes integration with clinical workflows, transparency through explainability, and suitability for deployment in under-resourced healthcare environments.

The network employs a three-tier processing structure consisting of data units, AI inference models, and explainability systems, collectively enabling complete neurological testing functionality. Each diagnostic module is implemented as a condition-specific expert system, trained exclusively on datasets tailored to that condition, thereby ensuring specialized accuracy beyond general-purpose AI solutions. Web-based deployment eliminates infrastructure limitations, allowing medical personnel to access expert-level diagnostics directly through standard internet browsers, without the need for specialized hardware, complex installations, or ongoing technical support.

2.2. Brain Tumor Classification and Detection Module

The brain tumor classification module adopts a dual-mode design, combining both 3D volumetric analysis and 2D slice-based processing for comprehensive tumor assessment. For 2D classification, two publicly available datasets, the Kaggle Brain Tumor MRI dataset and SciDB Brain Tumor dataset were merged, resulting in 7,023 individual MRI slices categorized into four tumor classes (glioma,

meningioma, pituitary tumor, no tumor).

The 2D classification system is built on the MobileNetV2 architecture (3,504,872 parameters), while for 3D volumetric analysis, the BraTS dataset was utilized, which includes multi-modal MRI scans and segmentation masks for Tumor Core (TC), Whole Tumor (WT), and Enhancing Tumor (ET). The module supports multi-class classification from 2D MRI and binary tumor presence detection from the BraTS dataset through specialized architectures optimized for medical imaging. SeruNet platform incorporates region attribution through XRAIs and offers interpretable visual explanation aligned with the radiologic reasoning for 2D and 3D prediction.

2.3. Stroke Detection Module

The stroke detection module follows a dual-framework design, combining image-based classification with a risk prediction model. For classification, the TEKNOFEST 2021 dataset, comprising 6,653 cranial CT images (4,428 normal, 1,131 ischemic stroke, 1,094 hemorrhagic stroke) was utilized. This image classification component employs the ResNet-18 architecture (11,689,512 parameters) for distinguishing between normal, ischemic stroke, and hemorrhagic stroke conditions.

The risk prediction module implements a machine learning pipeline using a clinically validated dataset of 35,000 patients with 17 predictive features including demographic variables and binary symptom indicators. Five algorithms were implemented: Random Forest, XGBoost, Gradient Boosting, Logistic Regression, and Support Vector Machine, all undergoing 5-fold stratified cross-validation followed by independent test set evaluation.

2.4. Alzheimer's Disease Detection with Bias Monitoring

The Alzheimer's disease module integrates both 2D severity classification and 3D volumetric analysis, along with bias monitoring. For 2D classification, 33,984 images representing four severity levels were used: MildDemented (8,960), ModerateDemented (6,464), NonDemented (9,600), and VeryMildDemented (8,960). Three CNN architectures EfficientNet-B4, ResNet-50, and MobileNet-V3 were systematically evaluated for multi-class severity assessment.

For 3D volumetric analysis, the OASIS-1 dataset was employed, featuring 436 subjects aged 18–96, including 100 Alzheimer's patients. The custom ImprovedSimple3DCNN model processes 32×32×32 voxel inputs for binary classification based on Clinical Dementia Rating scores.

Bias detection uses Pearson correlation to evaluate the relationship between predicted dementia outcomes and seven demographic/clinical parameters. Real-time monitoring is implemented to flag potential bias scenarios, specifically high-confidence predictions (>80%) of dementia in patients over 70 years old.

2.5. MS Risk Estimation with Two-Stage Model Architecture

The multiple sclerosis risk prediction module features an innovative two-stage architecture that separates demographic baseline risk from clinical risk modification. The dataset, sourced from Mexico City's National Institute of Neurology and Neurosurgery, includes 273 initial patients, of which 177 were retained after preprocessing and missing data handling.

The two-stage design mimics a natural diagnostic process. Stage 1 uses five demographic features (Age, Schooling, Gender, Breastfeeding History, Varicella History) to estimate population-level MS risk. Stage 2 incorporates clinical diagnostic data, such as symptoms, MRI lesion patterns, cerebrospinal fluid markers, and evoked potential results alongside Stage 1 outputs to calculate final, personalized risk estimates.

Both stages use logistic regression, selected for interpretability, probabilistic outputs, and clinical

relevance. This architecture enables clear separation of modifiable and non-modifiable risk factors, supports interpretable risk decomposition, reduces the dominance of demographic variables, and allows detailed SHAP-based attribution at both stages.

2.6. Explainable AI Integration and Implementation

SeruNet platform integrates a robust Explainable AI framework that incorporates SHAP and gradient saliency methods across all diagnostic modules. Each module applies these techniques in ways optimized for its analytic requirements. XRAI improves upon pixel-level attribution by performing region-level interpretation using a three-step process: Felzenswalb's graph-based segmentation, integrated gradient computation along interpolation paths, and iterative region selection that maximizes cumulative attribution gain per area. The implementation uses the Saliency library with customized wrappers to ensure precision. Module-specific applications include Brain Tumor 2D and Alzheimer's 2D using XRAI for region-based attribution maps; Brain Tumor 3D using Gaussian smoothing on segmentation masks; Stroke 2D using XRAI for CT-based classification; and SHAP TreeExplainer used for Stroke and LinearExplainer for MS risk prediction. The Alzheimer's 3D model applies gradient saliency by backpropagating absolute gradient contributions.

2.7. Clinical Web Application Development and Deployment

The clinical deployment framework uses a Gradio-based web application to provide browser-accessible diagnostic tools across all modules. SeruNet platform allows simultaneous access to brain tumor detection, stroke classification and risk prediction, Alzheimer's assessment with bias monitoring, and MS risk estimation, all through standard web browsers, without requiring specialized infrastructure or software. The application supports real-time processing with clinically acceptable response times, while maintaining consistent user experience. Standardized explainability protocols are applied uniformly across all diagnostic modules, making the system viable for immediate use in diverse and under-resourced healthcare settings. Additionally, the system provides protected data processing and role-based access control to support authorized user access and automatic logging of diagnostic results for compliance with medical data privacy policies and support for electronic health records systems. To be highly scalable, the system is containerized and deployed on cloud and on-premise servers and supports multi-user login concurrency and modular APIs to integrate with telemedicine systems and hospital information systems. The system supports persistent model monitoring and over-the-air upgrading to facilitate the integration of the new datasets, so the diagnostics model performance is state-of-the-art as the medical imaging technologies and clinical protocols advance.

3. Results

SeruNet (Smart Explainable Platform for Radiological Understanding) platform demonstrated strong performance across all four diagnostic modules. The brain tumor detection component achieved exceptional accuracy with the MobileNetV2 model reaching 98.09% accuracy for 2D multi-class classification across glioma, meningioma, pituitary tumor, and no tumor categories. The 3D segmentation component achieved approximately 70.57% mean Dice similarity coefficient, while the downstream MLP binary classifier reached 100% accuracy for tumor presence detection. XRAI explainability analysis consistently highlighted anatomically relevant regions corresponding to tumor locations across all test cases, providing clinically meaningful visualizations for diagnostic interpretation.

The stroke detection and risk prediction module demonstrated robust performance across both

classification and risk assessment tasks. The ResNet-18 model achieved 95% accuracy for stroke classification, with class-specific performance showing 96% precision for hemorrhagic stroke detection, 86% precision for ischemic stroke identification, and 98% precision for normal case classification. The risk prediction component demonstrated exceptional performance with XGBoost achieving 98.99% accuracy, 99.18% precision, 98.06% recall, and 99.95% ROC-AUC across 35,000 patient records.

Alzheimer's disease assessment yielded strong results across both 2D and 3D analysis approaches. For 2D severity classification, MobileNet-V3 achieved the highest performance with 99.18% accuracy, outperforming EfficientNet-B4 at 98.23% and ResNet-50 at 98.04%. The 3D binary classification model achieved 69.7% accuracy with 0.866 AUC, optimized for clinical screening applications with 97% precision for healthy class identification and 94% recall for dementia detection. Bias monitoring analysis revealed strong age correlation at 0.842, necessitating real-time alerting mechanisms for elderly patient assessments to ensure diagnostic transparency.

The multiple sclerosis risk prediction module demonstrated superior performance through its innovative two-stage architecture. The system achieved 0.909 ROC-AUC, substantially outperforming single-stage approaches and traditional machine learning methods. Stage 1 demographic baseline modeling achieved 0.659 AUC, while Stage 2 clinical integration elevated overall performance to 0.909 AUC, representing a 0.250 improvement attributed to clinical feature incorporation and architectural innovation.

4. Conclusion

This research demonstrates that SeruNet (Smart Explainable platform for Radiological Understanding) platform can provide comprehensive neurological diagnostic capabilities across multiple conditions within a single, accessible system. The integration of XRAI for clinical imaging, combined with bias-aware monitoring systems, establishes a framework for transparent and responsible AI deployment in healthcare applications. Web-based architecture eliminates traditional infrastructure barriers, enabling advanced diagnostic capabilities regardless of geographic location or available computational resources. The unified design approach reduces implementation complexity while maintaining specialized diagnostic accuracy through condition-specific expert systems. This work addresses fundamental limitations in current neurological AI systems including fragmentation, lack of interpretability, infrastructure dependence, absence of bias detection, and poor clinical integration.

Detailed methodology, comprehensive experimental results, and statistical validation for each neurological disorder have been completed as separate specialized studies and will be published as forthcoming papers. Future directions include expansion to neurological conditions, integration of multimodal data sources, enhancement of bias detection capabilities across broader demographic parameters, and development of clinical decision support protocols for diverse healthcare environments. SeruNet platform's modular architecture supports systematic scaling to include neurological diagnostic capabilities while maintaining the principles of accessibility, interpretability, and clinical utility.

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