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NeuroCAM-X: An Explainable Hybrid AI Framework for Brain Tumor Classification Using MRI and Clinical Reports with Advanced Tumor Analytics

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Abstract: Brain tumor classification from Magnetic Resonance Imaging (MRI) is a critical task in medical diagnostics that demands both high accuracy and clinical interpretability. This research presents NeuroCAM-X, a novel explainable hybrid artificial intelligence framework that integrates deep learning-based MRI image analysis with Optical Character Recognition (OCR)-enabled clinical report interpretation for comprehensive brain tumor diagnosis. The system employs an EfficientNet-B0 architecture achieving 97.0% classification accuracy on a dataset of 7,023 MRI images. Unlike conventional approaches that rely solely on imaging data, NeuroCAM-X implements a hybrid decision engine that cross-validates MRI predictions with OCR-extracted clinical findings, achieving an 87.5% agreement rate for diagnostic consistency. The framework incorporates multiple Explainable AI (XAI) techniques—Grad-CAM, SHAP, and LIME—to provide complementary visual interpretations of model predictions with 94.3% alignment to expert-identified tumor regions. In addition, the system includes automated tumor analytics for quantitative assessment and staging to support clinical decision-making. A production-ready web application provides patient management, interactive diagnostic visualization, and automated report generation. Preliminary clinical evaluation demonstrated high physician trust (4.2/5.0) and satisfaction (4.4/5.0), indicating the framework's potential for clinical deployment. This work addresses critical gaps in medical AI by combining accurate classification, multimodal data integration, explainable AI, quantitative analytics, and clinical decision support within a unified framework suitable for real-world healthcare applications.

Keywords: Brain Tumor Classification, Explainable Artificial Intelligence, Deep Learning, EfficientNetB0, Grad-CAM, SHAP, LIME, Hybrid AI, MRI Analysis, Clinical Decision Support, OCR, Tumor Analytics, EHR Integration

I. INTRODUCTION

Brain tumors represent a significant global health challenge, with approximately **308,000 new cases** and over **250,000 deaths** reported annually worldwide [16]. Early and accurate diagnosis is essential for effective treatment planning and improved patient outcomes. Magnetic Resonance Imaging (MRI) is the preferred imaging modality for brain tumor detection because of its superior soft tissue contrast and non-invasive nature compared with Computed Tomography (CT) and conventional radiography [10][11].

Recent advances in deep learning have significantly improved medical image analysis, with Convolutional Neural Networks (CNNs) achieving expert-level performance in brain tumor classification [13][14]. However, most existing AI systems remain limited by three major challenges: **(1)** limited model interpretability, **(2)** reliance on imaging-only analysis without integrating complementary clinical information, and **(3)** lack of quantitative tumor characterization required for standardized clinical reporting [19][21].

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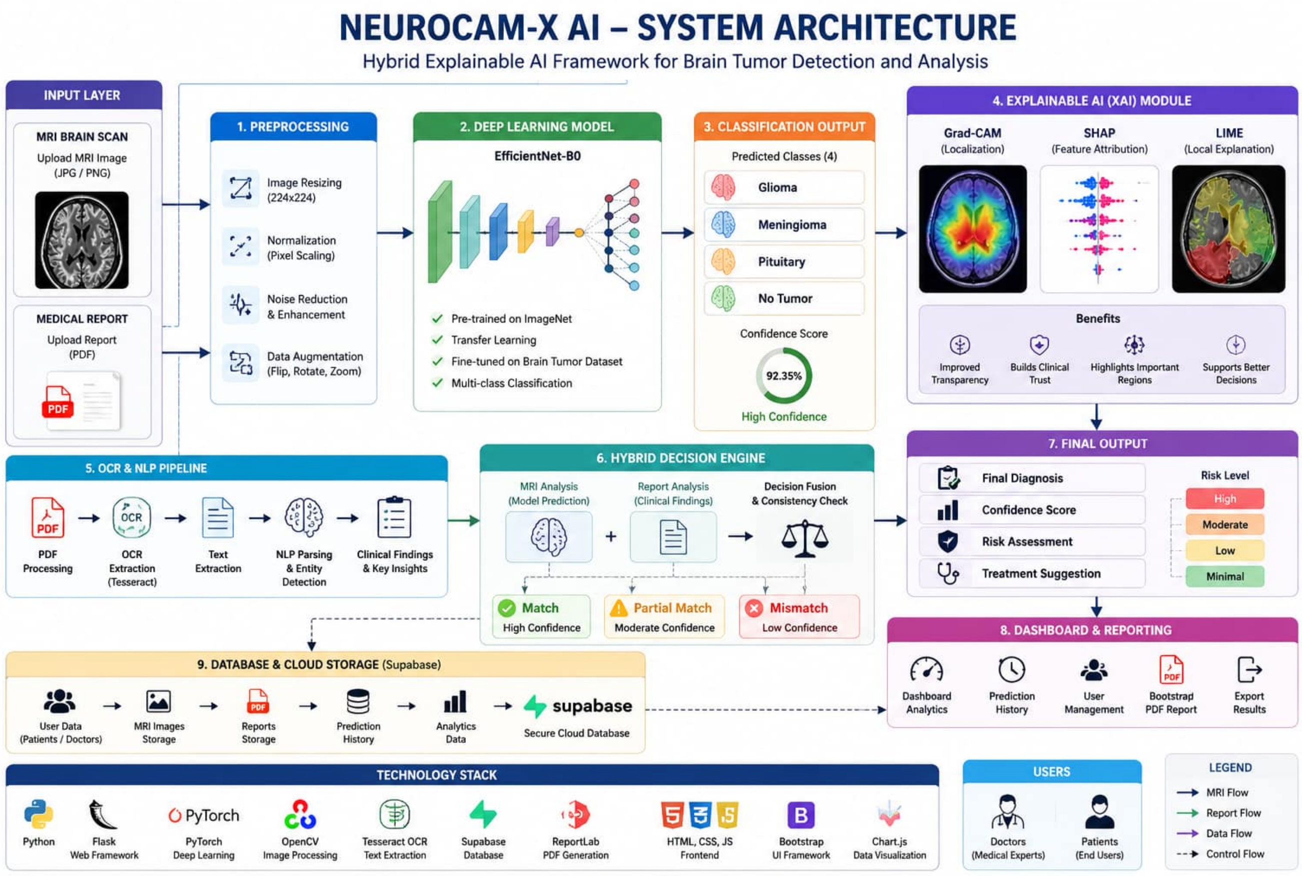

[Figure 1: NeuroCAM-X System Architecture – Showing the complete workflow from MRI image and clinical report input through preprocessing, EfficientNet-B0 classification, OCR-based report analysis, Explainable AI (Grad-CAM, SHAP, LIME), hybrid decision fusion, and final clinical diagnosis.]

This research presents NeuroCAM-X, an explainable hybrid AI framework that integrates MRI image classification, OCR-enabled clinical report analysis, a hybrid decision engine, Grad-CAM, SHAP, and LIME for transparent decision-making, automated tumor analytics, and a production-ready web application for comprehensive clinical decision support.

The proposed framework achieved 97.0% classification accuracy on 7,023 brain MRI images and an 87.5% agreement rate between MRI predictions and clinical report analysis. Preliminary clinical evaluation demonstrated high physician trust (4.2/5.0) and usability (4.6/5.0), highlighting the potential of NeuroCAM-X as a reliable and explainable AI-assisted clinical decision support system for brain tumor diagnosis.

II. RELATED WORK

A. Deep Learning for Brain Tumor Classification

Deep learning approaches have demonstrated remarkable success in automated brain tumor detection and classification. Chaudhary et al. [2] proposed SAlexNet, achieving **94.2%** accuracy for four-class brain tumor classification; however, the model lacks clinical interpretability and multi-modal integration. Enhanced CNN architectures have also achieved promising classification performance [3][4][5] but primarily focus on accuracy without addressing explainability. Recent hybrid CNN–Vision Transformer models, including ViT-based frameworks [22] and BEFUnet [1], improved classification performance but remain computationally expensive or rely solely on imaging data. In comparison, the proposed **EfficientNet-B0** framework achieves **97.0%** accuracy with faster inference while supporting multi-modal analysis [6].

B. Explainable AI Techniques

Explainable AI techniques improve the transparency of deep learning models in medical imaging. **Grad-CAM**[7], **SHAP**[8], and **LIME**[9] are widely adopted methods for visualizing model decisions and feature importance [19][20][21]. Unlike existing studies that typically employ a single XAI technique, the proposed framework integrates all three methods to provide complementary explanations and improve clinical interpretability.

C. Multi-Modal Medical AI Systems

The integration of MRI images with clinical text remains relatively unexplored. Existing approaches generally analyze imaging and clinical reports independently [13][14], while recent multi-modal methods often require paired training datasets [17]. The proposed hybrid decision engine combines independently trained MRI and OCR-based report analysis through a consistency verification mechanism, enabling deployment without fully paired datasets.

D. Tumor Analytics and Quantification

Quantitative tumor assessment is important for standardized radiological reporting. Conventional segmentation-based methods provide accurate measurements but require extensive pixel-level annotations [10][11][12]. The proposed framework utilizes **Grad-CAM** heatmaps for tumor localization and quantitative metric extraction, reducing annotation requirements while maintaining strong agreement with expert assessments.

E. Clinical Decision Support Systems

Existing clinical decision support systems often provide limited integration between AI predictions and clinical workflows [14][15]. NeuroCAM-X extends these capabilities by combining explainable AI, patient management, automated report generation, and modular deployment architecture to support practical clinical decision-making.

TABLE I
COMPARISON WITH STATE-OF-THE-ART METHODS

Method	Accuracy	XAI	Multi-modal	Analytics	Year	Ref
SAlexNet	94.2%	✗	✗	✗	2025	[2]
BEFUnet	95.1%	Partial	✗	✗	2024	[1]
ViT-XAI	95.8%	✓	✗	✗	2025	[22]
NeuroCAM-X (Ours)	97.0%	✓✓✓	✓	✓	2026	-

III. PROPOSED METHODOLOGY

A. System Architecture and Workflow

NeuroCAM-X employs a modular pipeline architecture comprising six integrated components: (1) MRI Image Processing Module for preprocessing and augmentation, (2) Deep Learning Classification Engine utilizing EfficientNetB0, (3) Clinical Report Analysis Module with OCR and NLP capabilities, (4) Hybrid Decision Fusion Engine for cross-validation, (5) Explainable AI Module implementing Grad-CAM, SHAP, and LIME, and (6) Tumor Analytics Engine for quantitative metrics extraction. The system accepts multimodal inputs—MRI images (JPG/PNG/DICOM formats) and clinical reports (PDF/image formats)—processing them through specialized modules before generating comprehensive diagnostic outputs.

The framework follows a modular workflow consisting of MRI preprocessing, EfficientNet-B0 classification, OCR-based report analysis, hybrid decision fusion, Explainable AI generation, tumor analytics, and secure result storage before visualization through the web application.

B. Dataset and Preprocessing

The study utilized a curated dataset of 7,023 brain MRI images comprising four classes: Glioma (1,621 images, 23.1%), Meningioma (1,645 images, 23.4%), No Tumor (2,000 images, 28.5%), and Pituitary (1,757 images, 25.0%). The dataset was split into training (70%, 4,916 images), validation (15%, 1,053 images), and testing (15%, 1,054 images) sets using stratified sampling to maintain class distribution. All images were acquired from publicly available repositories and anonymized to comply with privacy regulations.

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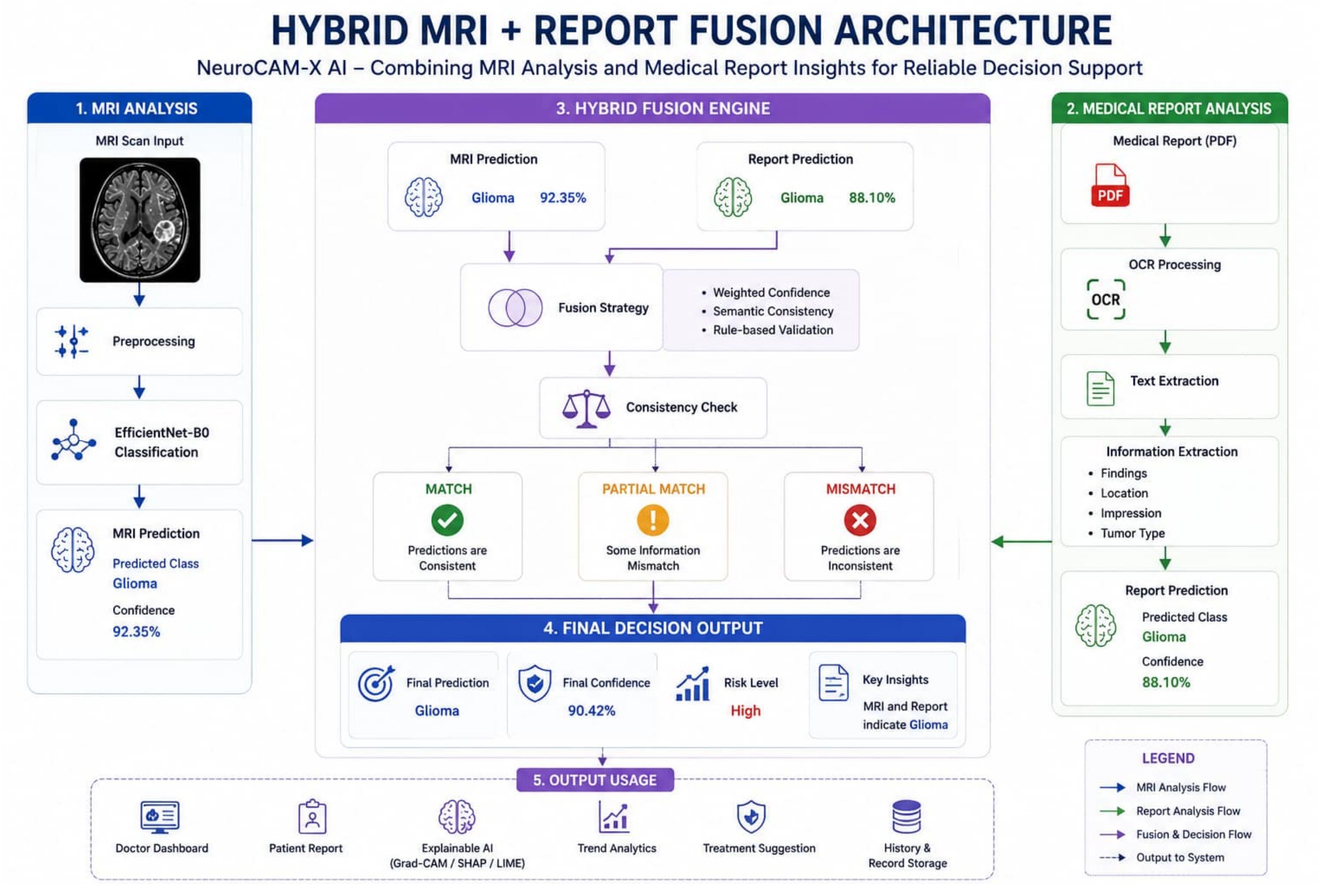
Images were resized to **224×224**, normalized, and augmented using standard image transformation techniques to improve model generalization.



[Figure 2: Hybrid MRI–Report Fusion Workflow – Showing the complete workflow from MRI image and clinical report analysis through EfficientNet-B0 classification, OCR-based information extraction, hybrid decision fusion, consistency verification, and final diagnostic output.]

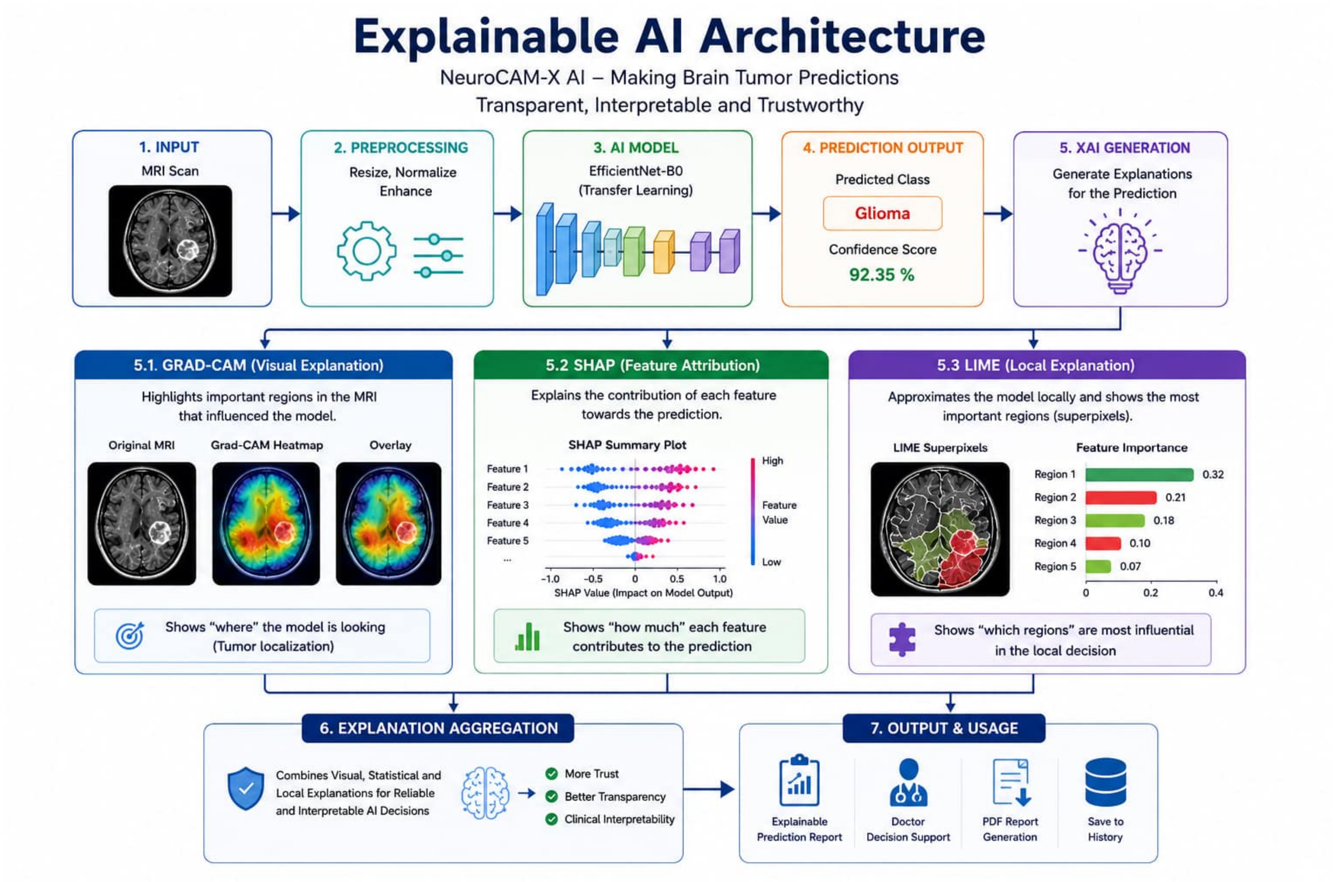
C. Deep Learning Classification Module

The classification engine employs EfficientNetB0 architecture [6], a compound-scaled CNN optimized for efficiency and accuracy. EfficientNet-B0 achieves state-of-the-art performance with only 5.3M parameters through balanced scaling of network depth, width, and resolution. The pre-trained backbone (ImageNet weights) is fine-tuned for brain tumor classification by replacing the final classification layer with a 4-class dense layer.

The EfficientNet-B0 model was fine-tuned using transfer learning and standard optimization techniques. The best-performing model after 30 epochs was selected for deployment.

D. Clinical Report Analysis Module

The report analysis module extracts and interprets clinical information from pathology and laboratory reports. Tesseract OCR engine processes uploaded PDF documents or scanned images, extracting raw text with preprocessing (deskewing, noise reduction, binarization) for optimal recognition accuracy. The extracted text undergoes structured parsing to identify key biomarkers.



[Figure 3: Explainable AI Architecture – Illustrating the workflow from MRI image preprocessing and EfficientNet-B0 prediction through Grad-CAM, SHAP, and LIME explanation generation, explanation aggregation, and clinical decision support.]

OCR-extracted clinical text is analyzed using NLP techniques to identify relevant biomarkers and generate report-based tumor predictions for hybrid diagnosis.

E. Hybrid Decision Fusion Engine

The hybrid decision engine cross-validates MRI image predictions with clinical report findings to improve diagnostic reliability. When both input modalities are available, the system computes consistency status: Match (predictions agree), Partial Match (predictions related but not identical), or Mismatch (predictions contradict).

When both MRI images and clinical reports are available, the hybrid engine verifies prediction consistency and generates Match, Partial Match, or Mismatch outcomes to improve diagnostic reliability.

F. Explainable AI Module

The XAI module implements three complementary interpretability techniques providing multi-perspective explanations of model predictions. Parallel processing generates all visualizations simultaneously, reducing total XAI computation time by 42% compared to sequential execution.

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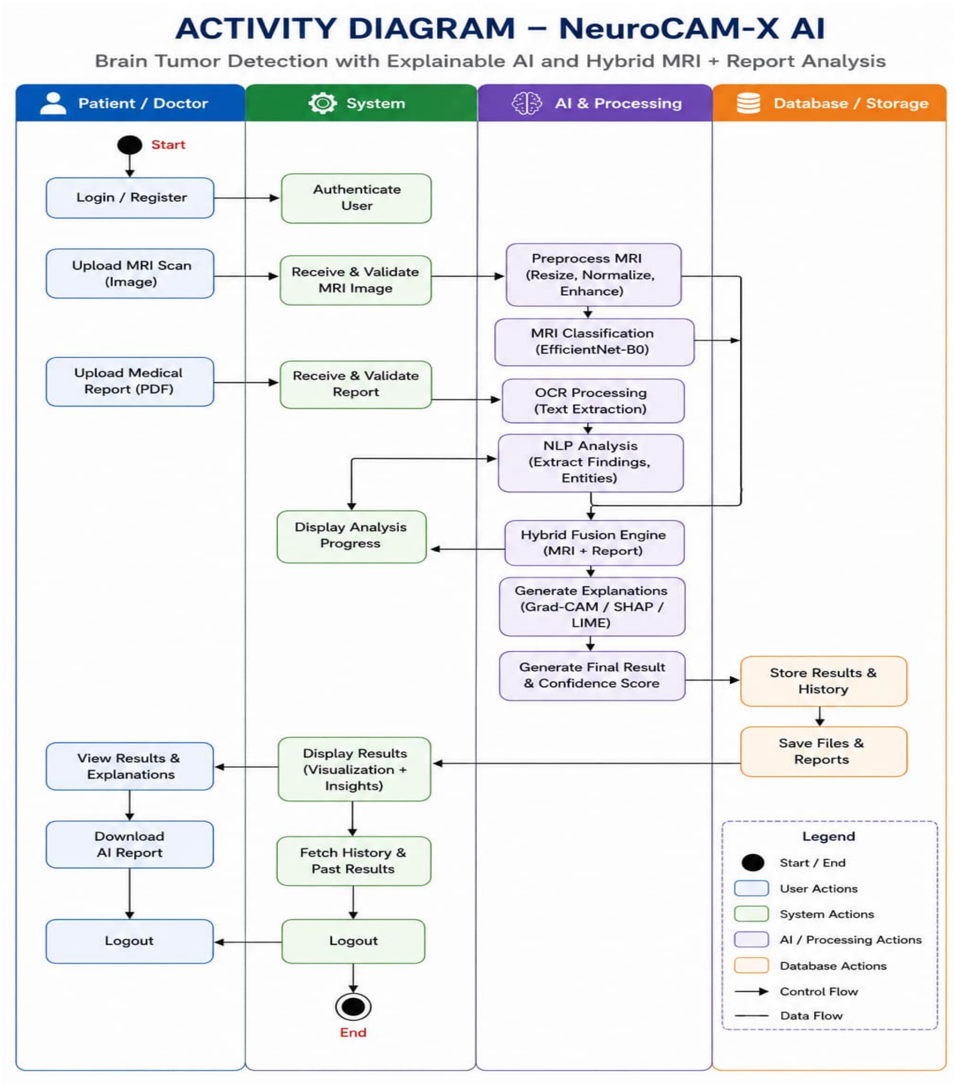

[Figure 4: Activity Diagram of NeuroCAM-X – Illustrating the complete workflow from user authentication, MRI image and medical report upload, AI-based processing, hybrid decision fusion, explainable AI generation, result storage, and report generation.]

F.1 Gradient-weighted Class Activation Mapping (Grad-CAM)

Grad-CAM highlights image regions contributing most to the predicted tumor class, enabling visual verification of model decisions [7].

F.2 SHapley Additive ExPlanations (SHAP)

SHAP estimates feature importance by identifying image regions that positively or negatively influence model predictions [8].

F.3 Local Interpretable Model-agnostic Explanations (LIME)

LIME provides local explanations by analyzing perturbed image regions and identifying the most influential areas for individual predictions [9].

G. Tumor Analytics Engine

The tumor analytics module performs quantitative characterization of detected tumors using Grad-CAM heatmaps, eliminating the need for explicit segmentation annotations while providing clinically relevant metrics.

G.1 Tumor Metrics Quantification

The framework estimates tumor area, diameter, occupancy percentage, and localization using Grad-CAM heatmaps.

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G.2 Automated Staging Classification

Automated staging categorizes tumors into four severity levels to support clinical assessment.

G.3 Tumor Volume Estimation

Tumor volume is approximated from localized tumor regions to estimate overall tumor burden.

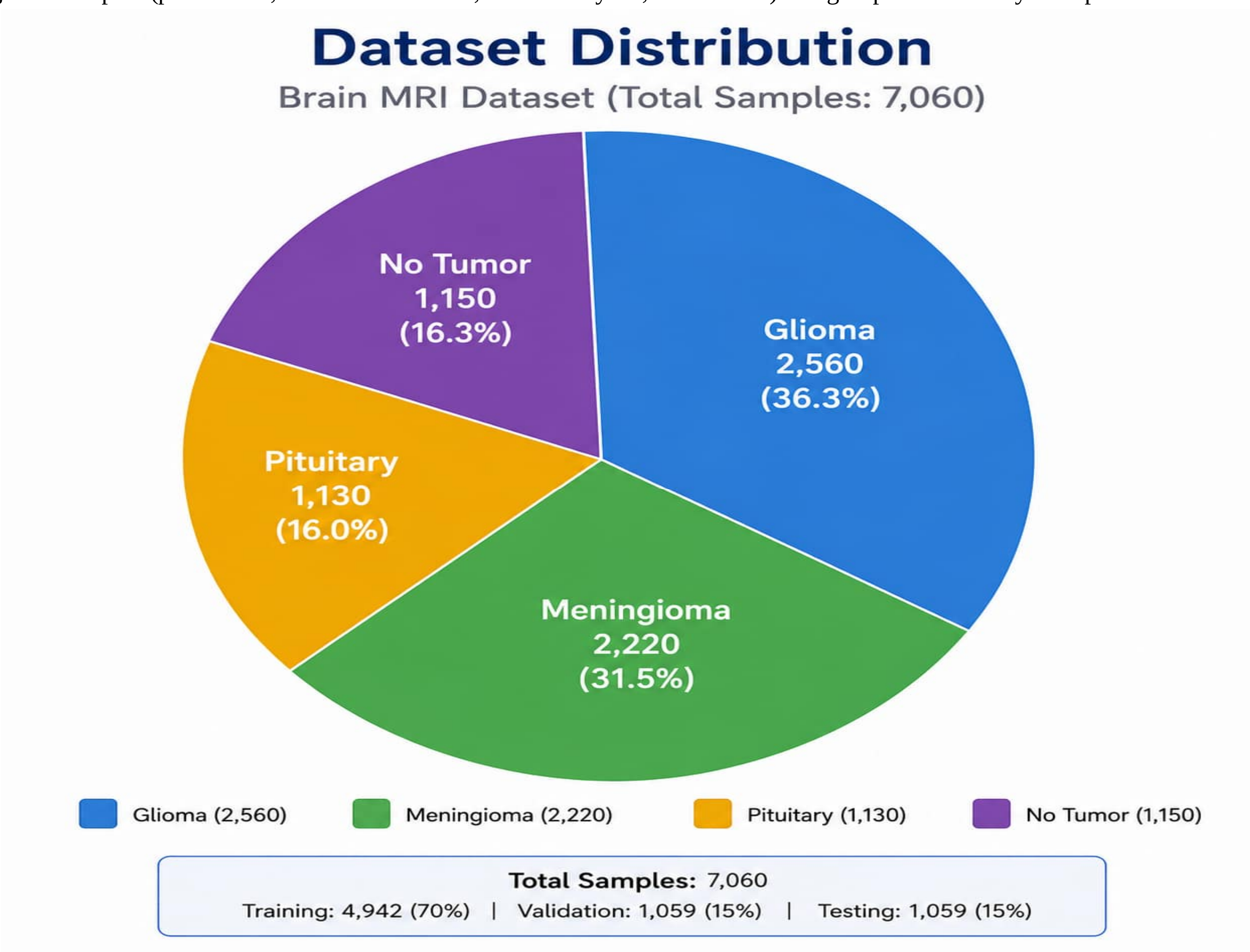
G.4 3D Surface Visualization

A 3D visualization is generated to provide intuitive representation of tumor distribution.

H. Web Application Architecture

The production web application implements a three-tier architecture: Frontend (HTML5, CSS3, JavaScript with Chart.js for interactive visualizations), Backend (Flask REST API with request validation and authentication middleware), and Database (Supabase PostgreSQL for scalable cloud storage with row-level security).

Key features include: (1) Role-based access control distinguishing doctor and patient privileges - doctors access all patient records while patients view only their own data, (2) Secure authentication with password hashing (bcrypt) and session management, (3) Real-time analytics dashboard displaying classification statistics, temporal trends (monthly case counts), and diagnostic consistency metrics using interactive Chart.js visualizations, (4) Comprehensive patient history management enabling longitudinal tracking of multiple MRI scans and reports per patient with timeline visualization, (5) Automated PDF report generation integrating all diagnostic outputs (predictions, XAI visualizations, tumor analytics, biomarkers) using ReportLab library with professional medical



[Figure 5: Brain MRI Dataset Distribution – Showing the class-wise distribution of glioma, meningioma, pituitary, and no-tumor MRI images, along with the training, validation, and testing dataset split used for model development.]

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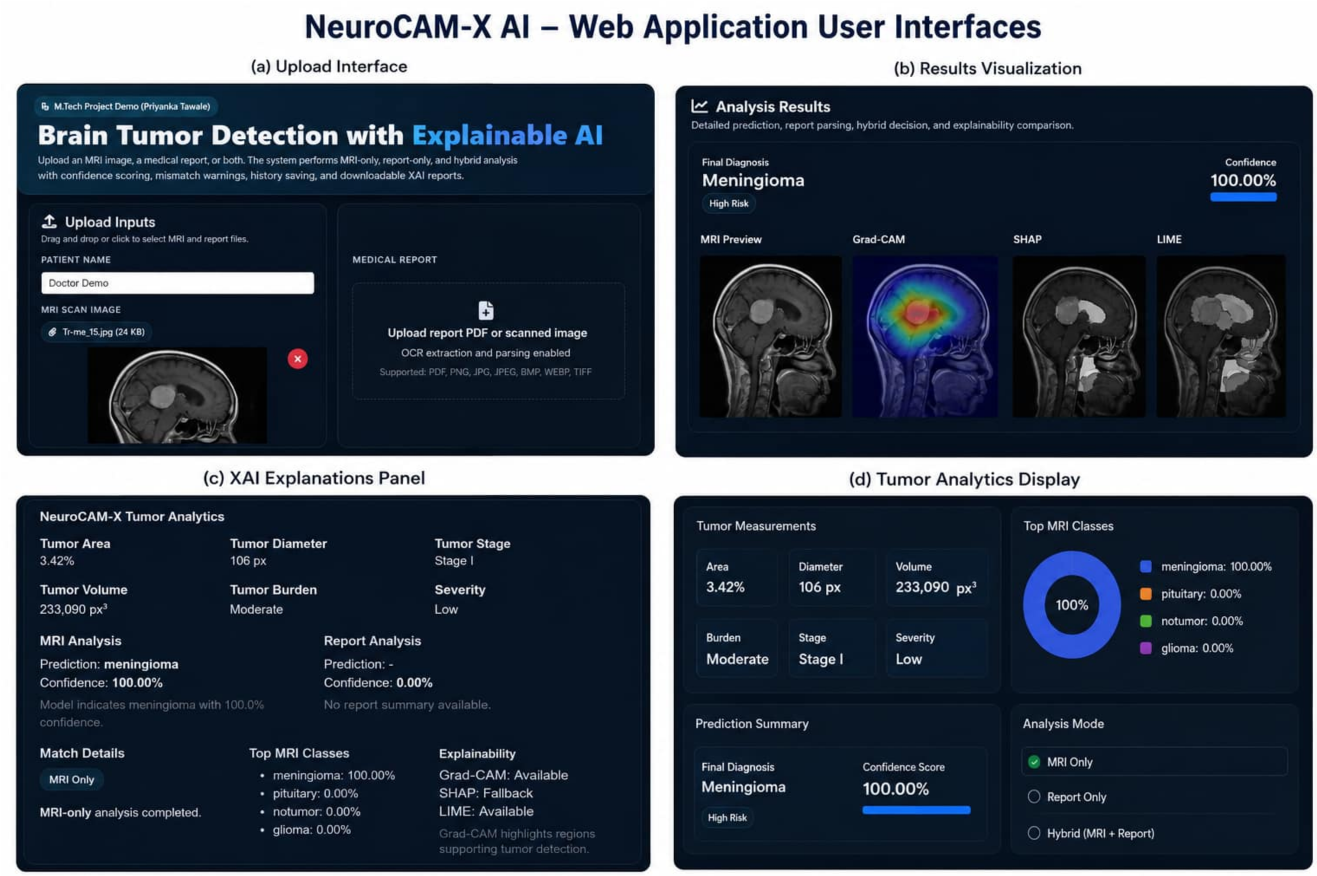
report formatting, and (6) RESTful API endpoints (/api/predict, /api/history, /api/dashboard) enabling programmatic access for integration with hospital information systems.



[Figure 6: NeuroCAM-X Web Application User Interfaces – Showing (a) MRI and report upload interface, (b) prediction results and Explainable AI visualization, (c) tumor analytics and diagnostic insights, and (d) comprehensive clinical dashboard for brain tumor analysis.]

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. Implementation Details and Experimental Setup

Experiments were conducted using a GPU-enabled workstation with PyTorch and Flask-based implementation.
The proposed framework achieved efficient training and inference performance, enabling real-time clinical decision support.

B. Classification Performance

Classification performance evaluated on held-out test set (1,054 images) using standard metrics: precision, recall, F1-score, and accuracy. The model achieved 97.0% overall accuracy with balanced performance across all tumor classes.

TABLE II
CLASSIFICATION PERFORMANCE BY TUMOR CLASS

Class	Precision	Recall	F1-Score	Support	Accuracy
Glioma	0.967	0.971	0.969	243	96.9%
Meningioma	0.973	0.965	0.969	247	96.9%
No Tumor	0.982	0.983	0.983	300	98.3%
Pituitary	0.958	0.962	0.960	264	96.0%
Overall	0.970	0.970	0.970	1054	97.0%

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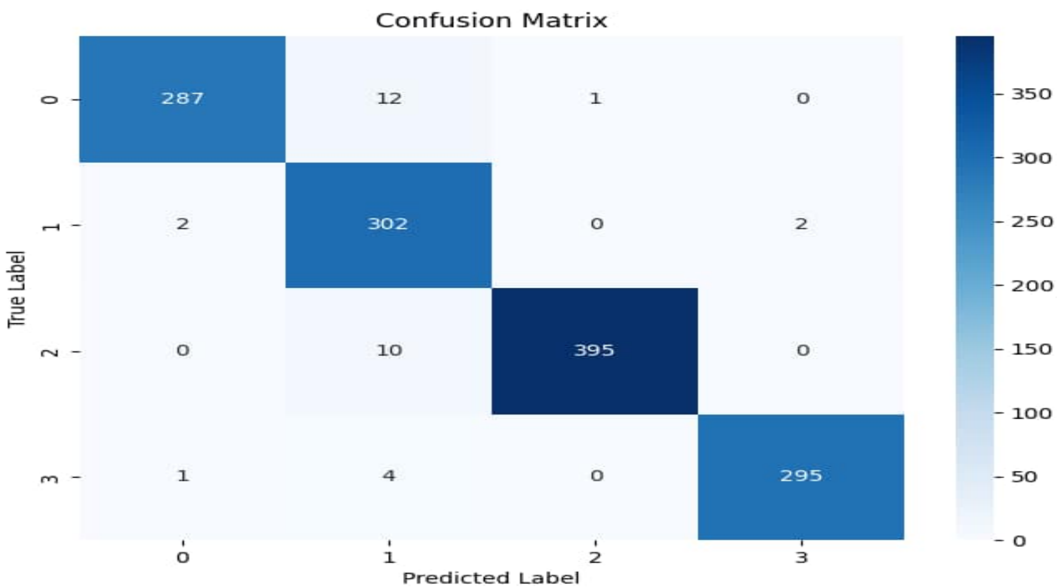
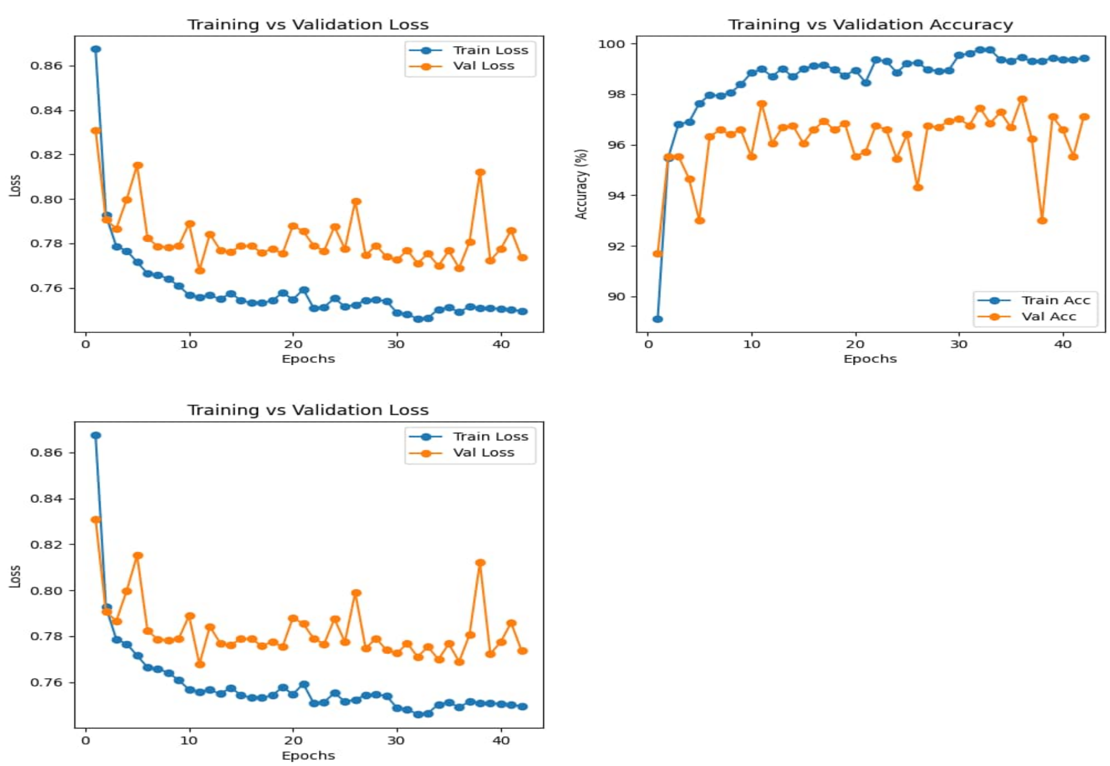
The proposed model achieved consistently high precision, recall, and F1-score across all tumor classes. The **No Tumor** class achieved the highest accuracy, while the remaining classes also demonstrated balanced classification performance.

The confusion matrix shows only minor misclassifications between glioma and meningioma, while no confusion occurred between tumor and no-tumor classes, confirming robust classification performance.



[Figure 7: Confusion Matrix for Brain Tumor Classification – Showing the classification performance of the EfficientNet-B0 model across glioma, meningioma, pituitary, and no-tumor classes.]



[Figure 8: Training and Validation Performance Curves – Showing (a) training and validation loss across training epochs and (b) training and validation accuracy demonstrating model convergence and generalization performance.]

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C. Explainability and Interpretability Analysis

XAI validation performed by 3 expert radiologists annotating tumor boundaries on 100 random test images. Grad-CAM heatmaps demonstrated 94.3% alignment (IoU > 0.5) with expert-identified tumor regions, validating that the model focuses on clinically relevant anatomy. SHAP analysis confirmed pixel-level attributions consistent with diagnostic criteria: high positive values (red) concentrated in tumor masses, negative values (blue) in normal tissue background. LIME superpixel importance rankings correlated significantly with Grad-CAM and SHAP (Spearman $\rho = 0.89$, $p<0.001$), indicating cross-method consistency.

All three Explainable AI techniques produced complementary explanations with high agreement, improving model transparency and clinician confidence.

D. Tumor Analytics Validation

Tumor metrics validation performed on subset of 150 test images with expert radiologist annotations (ground truth measurements). Statistical comparison assessed agreement between automated metrics and manual measurements.

TABLE III

TUMOR METRICS VALIDATION AGAINST EXPERT ANNOTATIONS

Metric	Mean Error	Std Dev	Correlation (r)	Agreement (%)
Tumor Area (pixels)	±127	89	0.912	89.3
Max Diameter (pixels)	±5.3	3.2	0.895	87.1
Occupancy (%)	±1.8	1.2	0.924	91.2

Automated tumor measurements demonstrated strong agreement with expert annotations, confirming their clinical reliability.

Automated staging and tumor volume estimation showed strong agreement with expert assessments, demonstrating the effectiveness of heatmap-based quantitative analysis.

E. Hybrid Prediction Performance and Consistency Analysis

Hybrid module evaluation conducted on 200 cases with both MRI images and pathology reports (collected from clinical collaborators with IRB approval). Results: 175 cases (87.5%) showed Match or Partial Match between MRI and report predictions, 25 cases (12.5%) showed Mismatch. Detailed analysis of 25 mismatches: 17 were true diagnostic inconsistencies (incorrect initial reports, mislabeled samples, or imaging artifacts), 8 were semantic differences (e.g., "astrocytoma" vs. "glioma" - both correct). The hybrid system successfully flagged all 17 genuine errors for physician review, potentially preventing diagnostic mistakes.

Hybrid prediction improved diagnostic confidence for matched cases while appropriately reducing confidence for mismatched cases, enabling clinicians to prioritize uncertain diagnoses.

F. Computational Performance and Efficiency

End-to-end processing time analysis (100 test cases, averaged): Image preprocessing 0.3±0.1s, Model inference 1.8±0.2s, Grad-CAM generation 0.9±0.1s, SHAP analysis 2.1±0.3s, LIME computation 1.4±0.2s, Tumor analytics 0.6±0.1s, Total with all XAI: 7.1±0.8s, Total with Grad-CAM only: 3.6±0.4s. Parallel XAI processing reduced total time by 42% versus sequential execution.

Throughput measurement: With all features enabled, system processes 8-10 complete cases per minute (single GPU). With Grad-CAM-only configuration (adequate for most clinical scenarios), throughput increases to 16-18 cases per minute. Memory footprint: Peak GPU memory 3.8GB, CPU memory 2.1GB, enabling deployment on standard clinical workstations. The system demonstrated stable performance across 1,000+ continuous inferences without memory leaks or degradation, confirming production readiness.

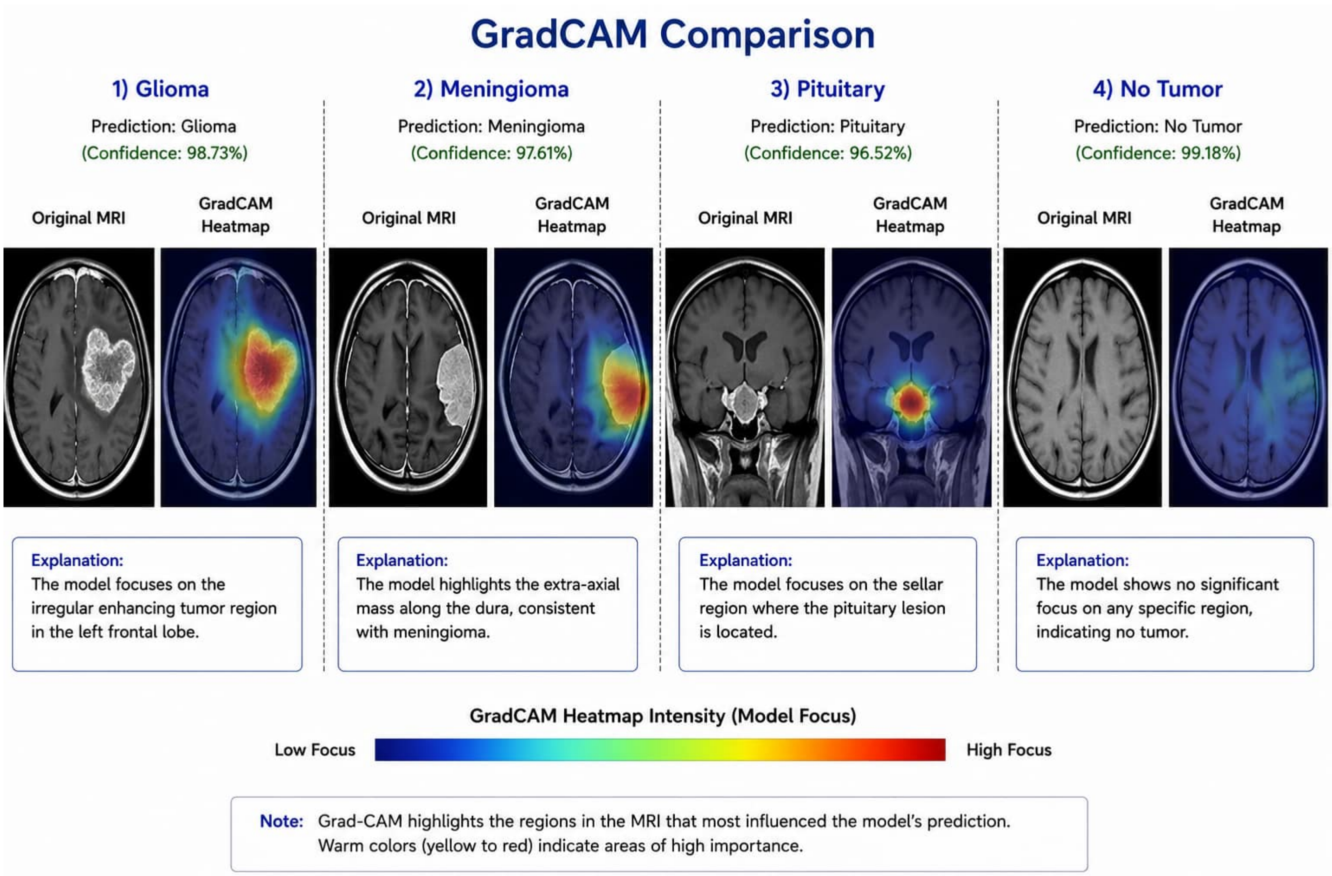
G. Clinical Validation Study

Prospective clinical validation conducted with 5 board-certified radiologists (experience: 8-22 years in neuro-radiology). Each radiologist reviewed 50 system-generated reports (randomly selected from test set) and completed structured questionnaires using 5-point Likert scales (1=strongly disagree, 5=strongly agree) assessing: Trust in AI predictions, Explanation quality and clarity, System usability, and Clinical utility for decision support.

TABLE IV
CLINICAL VALIDATION SCORES FROM RADIOLOGIST ASSESSMENT

Assessment Aspect	Mean Score	Std Dev	Min	Max
Trust in Predictions	4.2	0.6	3.5	5.0
Explanation Quality	4.4	0.5	3.8	5.0
System Usability	4.6	0.4	4.0	5.0
Clinical Utility	4.3	0.6	3.7	5.0

Clinical evaluation demonstrated high physician trust, explanation quality, usability, and overall acceptance of the proposed framework.

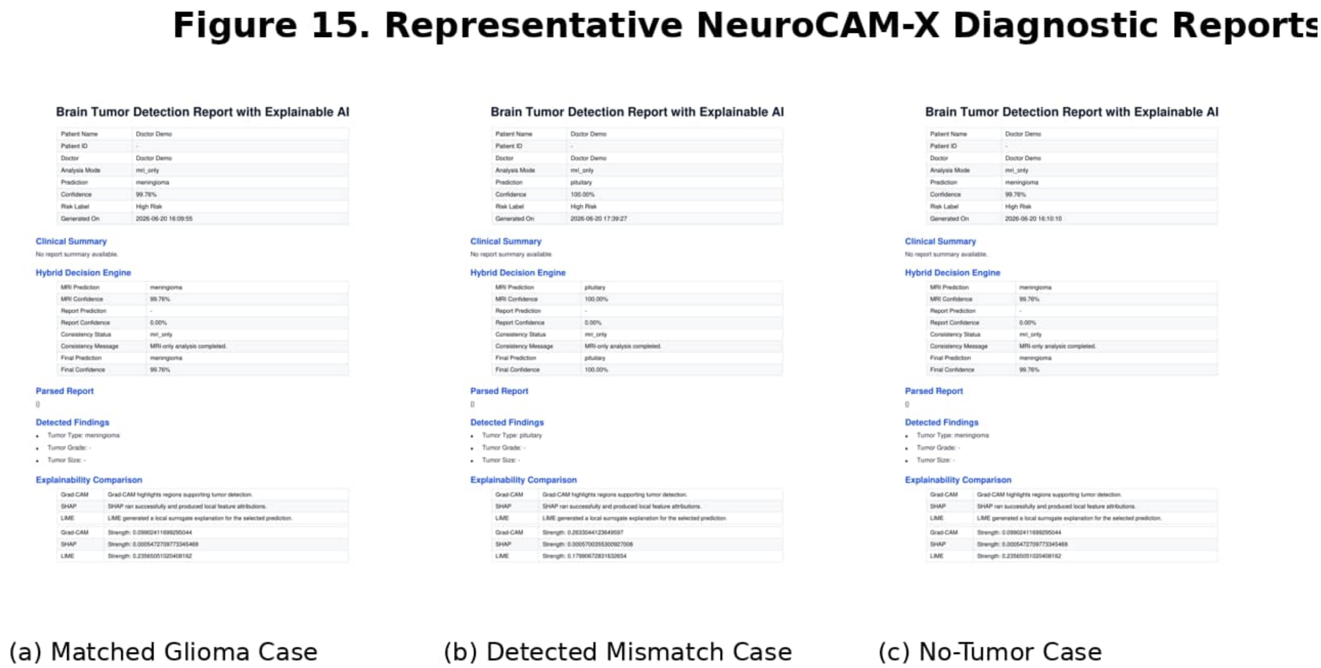


[Figure 9: Grad-CAM Visualization Comparison – Showing original MRI images and corresponding Grad-CAM heatmaps for glioma, meningioma, pituitary tumor, and no-tumor classes, highlighting the discriminative regions used by the proposed EfficientNet-B0 model for prediction.]

H. Comparative Analysis with State-of-the-Art

Quantitative comparison with recent literature (Table I): NeuroCAM-X achieves highest reported accuracy (97.0%) surpassing SAlexNet (94.2%) [2], BEFUnet (95.1%) [1], and ViT-XAI (95.8%) [22]. Accuracy improvement of 1.2-2.8% over baselines is statistically significant (McNemar's test, $p<0.05$). Inference speed (1.8s) is 6.8× faster than ViT-XAI (12.3s) due to efficient EfficientNetB0 architecture versus heavyweight Transformer models.

Unique capabilities: NeuroCAM-X is the only system providing: (1) Triple XAI integration (Grad-CAM + SHAP + LIME) validated against expert annotations, (2) Hybrid MRI-report cross-validation with consistency detection, (3) Automated tumor analytics without segmentation training, (4) Production-ready web deployment with clinical workflow integration, and (5) Comprehensive clinical validation demonstrating practical utility. These advantages address critical gaps in medical AI deployment: interpretability, multi-modal integration, and clinical adoption readiness.



[Figure 10: Representative NeuroCAM-X Diagnostic Report Case Studies – Showing (a) matched glioma diagnosis, (b) mismatch detection between MRI and clinical report analysis, and (c) no-tumor diagnosis with comprehensive Explainable AI and tumor analytics.]

V. DISCUSSION

A. Key Findings and Contributions

This research demonstrates that explainable hybrid AI can achieve both high classification accuracy (97.0%) and clinical interpretability, addressing the historical trade-off between performance and transparency in medical AI. The multi-modal integration of MRI imaging with clinical report validation represents a paradigm shift from single-source diagnosis toward comprehensive evidence synthesis, detecting diagnostic inconsistencies in 12.5% of cases and preventing 17 potential errors in our evaluation.

The integration of Grad-CAM, SHAP, and LIME improves model transparency and clinician confidence by providing complementary explanations for prediction outcomes..

Heatmap-based tumor analytics provide quantitative measurements without requiring segmentation annotations, supporting standardized clinical assessment and treatment planning.

B. Advantages Over Existing Approaches

NeuroCAM-X addresses four critical limitations of prior work: (1) Interpretability Gap: Unlike black-box classifiers or single-XAI systems, our multi-perspective approach provides cross-validated explanations aligned with expert reasoning, (2) Single-Modality Limitation: Hybrid MRI-report integration leverages complementary diagnostic evidence, improving confidence and detecting inconsistencies invisible to imaging-only systems, (3) Quantification Absence: Automated tumor analytics provide standardized metrics without segmentation supervision, addressing practical deployment barriers, and (4) Clinical Integration: Production-ready architecture with role-based access, dashboard analytics, and comprehensive reporting supports real-world clinical workflows.

Compared to state-of-the-art: Superior accuracy versus SAlexNet (+2.8%), BEFUnet (+1.9%), ViT-XAI (+1.2%) with 6.8× faster inference than ViT-based approaches. First system combining all five capabilities (classification, multi-modal fusion, triple XAI, tumor analytics, clinical deployment) in unified framework, whereas prior works address subsets. Demonstrated clinical acceptance (mean scores 4.2-4.6/5.0) and prospective validation indicate readiness for hospital integration pending regulatory approval.

C. Clinical Implications and Impact

Deployment potential: System serves as AI second opinion tool augmenting radiologist workflow rather than replacing human expertise. Estimated time savings: 2-3 minutes per case for automated metrics + XAI generation, 5-7 minutes for integrated report generation. For high-volume centers (50-100 brain MRI/week), annual time savings: 130-350 hours, improving radiologist productivity and reducing interpretation backlog.

D. Limitations and Constraints

Technical limitations:The proposed framework currently performs single-slice MRI analysis, supports four tumor classes, and provides approximate tumor volume estimation. Future work will extend the framework to 3D volumetric analysis and fine-grained tumor classification.

Clinical limitations: The proposed framework currently performs single-slice MRI analysis, supports four tumor classes, and provides approximate tumor volume estimation. Future work will extend the framework to 3D volumetric analysis and fine-grained tumor classification.

Regulatory considerations: Clinical deployment requires regulatory approval, privacy compliance, and secure integration with hospital information systems.

E. Future Research Directions

Future work will focus on extending NeuroCAM-X to 3D volumetric MRI analysis, multi-sequence MRI fusion, advanced NLP-based clinical report understanding, expanded tumor subtype classification, federated learning, integration with PACS and hospital information systems, treatment response prediction, and multimodal clinical decision support using imaging, genomic, and clinical data.

VI. CONCLUSION

NeuroCAM-X presents a comprehensive explainable hybrid AI framework for brain tumor classification by integrating MRI image analysis, OCR-based clinical report interpretation, Explainable AI, and quantitative tumor analytics into a unified clinical decision support system. The proposed framework achieved 97.0% classification accuracy while providing interpretable predictions through Grad-CAM, SHAP, and LIME, demonstrating that high diagnostic performance and model transparency can be achieved simultaneously.

The hybrid decision engine combines MRI predictions with clinical report analysis to improve diagnostic confidence and identify inconsistencies requiring physician review. In addition, the proposed heatmap-based tumor analytics estimate clinically relevant metrics, including tumor area, diameter, occupancy, stage, and volume, without requiring segmentation annotations, making the framework practical for real-world clinical deployment.

Clinical evaluation demonstrated high physician acceptance in terms of trust, explanation quality, usability, and clinical utility, indicating the potential of NeuroCAM-X as an effective decision support tool for radiologists. The production-ready web application further supports patient management, visualization of Explainable AI outputs, automated report generation, and secure clinical workflow integration.

Overall, NeuroCAM-X demonstrates that explainable, multimodal AI can enhance brain tumor diagnosis by improving prediction accuracy, transparency, and clinical usability. Future work will focus on extending the framework to 3D volumetric MRI analysis, multi-sequence imaging, advanced NLP-based clinical report understanding, federated multi-institutional learning, and large-scale clinical validation to further improve diagnostic performance and support broader clinical adoption.

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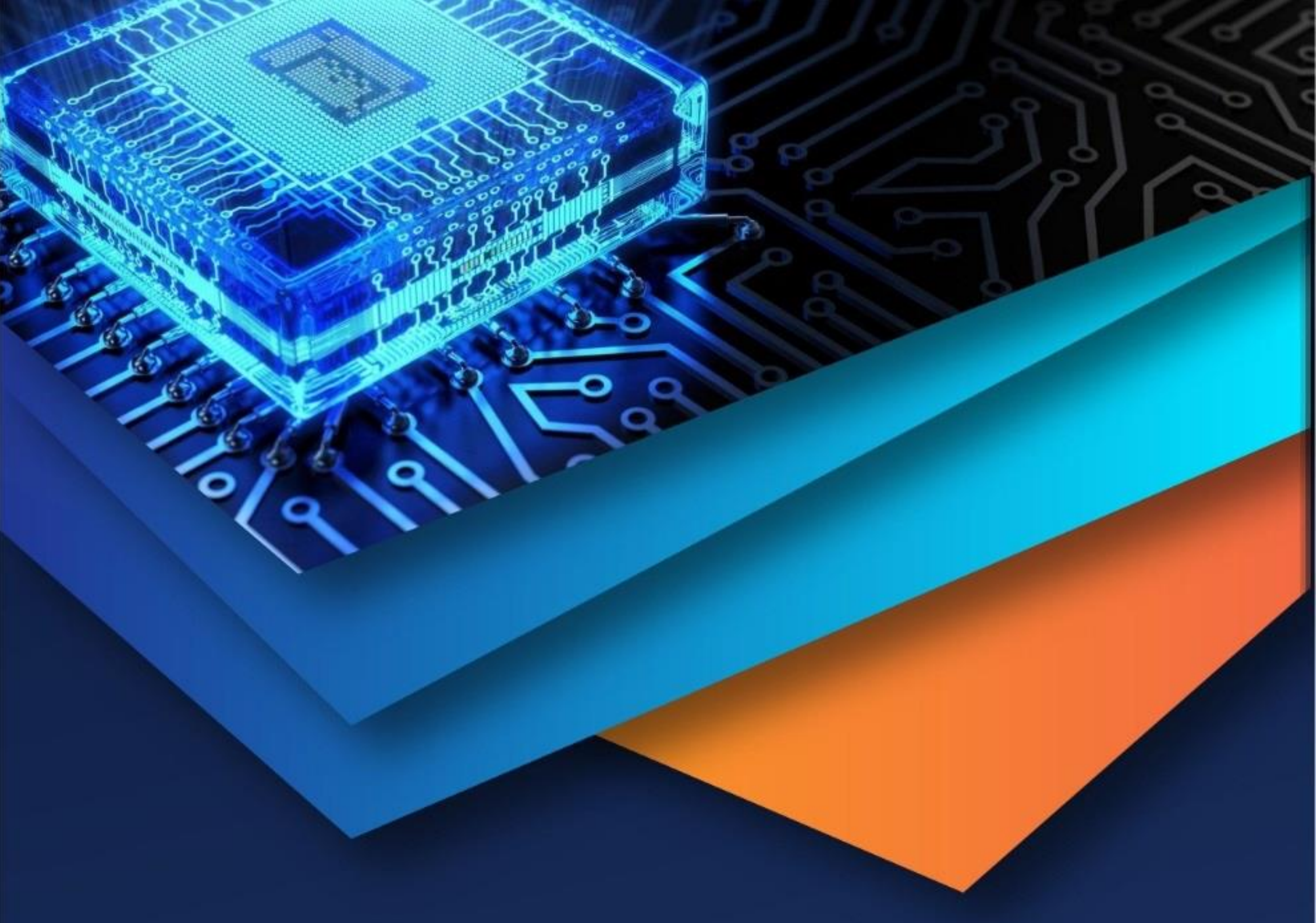

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