International Journal of Engineering and Information Systems (IJEAIS)
ISSN: 2643-640X
Vol. 10 Issue 5 May - 2026, Pages: 94-101

AI-Powered brain cancer prediction web-application

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Abstract— Brain cancer is a life-threatening neurological condition that requires early and accurate diagnosis to improve patient survival and treatment outcomes. In many low-resource countries, including Tanzania, the diagnosis of brain tumors is severely constrained by a critical shortage of radiologists and neurosurgeons, limited access to advanced diagnostic tools, and delays in clinical decision-making. This review presents Neuropredict, an AI-powered brain cancer prediction system designed to support healthcare professionals by automating the analysis of brain MRI scans using deep learning techniques; the manuscript describes planned methods, anticipated evaluations, and a roadmap for future validation. The system integrates a convolutional neural network (CNN) model within a full-stack web application to classify MRI images into binary outcomes indicating the presence or absence of brain cancer. The development of Neuropredict will follow the CRISP-DM methodology, encompassing data understanding, preprocessing, modeling, evaluation, and deployment. MRI datasets will be obtained from publicly available repositories; where permissible, these will be supplemented with locally sourced, de-identified MRI images from Tanzanian hospitals to enhance contextual relevance to enhance contextual relevance. Image preprocessing techniques such as resizing, normalization, and data augmentation will be applied to improve model robustness and generalization. The trained CNN model will be deployed through a FastAPI backend and a user-friendly web interface to enable near real-time clinical use in pilot settings. System validation will be conducted using external MRI scans to assess predictive performance, measuring confidence scores and agreement with traditional clinical assessments. If validated, AI-assisted diagnosis could reduce diagnostic time while maintaining high accuracy, thereby helping to alleviate the burden on limited medical specialists. Despite its promising performance, the system will initially focus on binary classification and may not support tumor grading or full DICOM/PACS integration until later development. Overall, this review highlights the potential of AI-driven diagnostic tools like Neuropredict to enhance early brain cancer detection, particularly in resource-constrained healthcare settings, while emphasizing the need for further validation, explainability, and large-scale clinical deployment.

Keywords— Brain cancer Detection, Magnetic Resonance Imaging (MRI), Artificial Intelligence,

Deep Learning, Convolutional Neural Networks (CNN), AI- Assisted Medical Diagnosis, Medical Image Classification.

1. INTRODUCTION

Early and accurate detection of brain tumors is critical to patient prognosis and treatment planning, yet many low- and middle-income countries face severe shortages of specialist radiologists and neurosurgeons that impede timely diagnosis and care. In Tanzania, for example, national reporting indicates an acute deficit of neurosurgical and radiology capacity, motivating solutions that augment clinical workflows and extend diagnostic reach. Neuropredict is an AI-driven MRI analysis system intended to support clinicians in resource-constrained settings by automatically classifying brain MRI scans as "tumor" or "no tumor," integrating a convolutional neural network (CNN) model with a FastAPI backend and a web frontend to deliver near real-time predictions. AI and deep learning methods particularly CNNs and transfer-learning approaches have demonstrated strong image classification and tumor segmentation, offering pathways to reduce interpretation time and to flag cases that require urgent review. However, clinical translation requires careful attention to data heterogeneity, image formats (e.g., DICOM), explainability, and fairness across populations; prior work has documented pitfalls such as over-optimistic performance estimates and demographic biases when models are trained on limited or non-representative datasets. This review places Neuropredict within that broader context: it summarizes the technical approach (data preprocessing, modeling, deployment), outlines planned real-world validation using locally sourced MRI images, and identifies methodological and ethical gaps that must be addressed to advance safe, equitable deployment in Tanzania and similar settings.

2. BACKGROUND

Brain tumors require multidisciplinary care and early detection to improve survival and functional outcomes.[1] In many low-resource environments, diagnostic delays arise from limiteity, uneven imaging capacity, and logistical barriers to referral and follow-up. [2]National reporting from Tanzania highlights an extreme shortage of neurosurgical and radiology specialists (e.g., single digit counts of neurosurgeons and a small cadre of radiologists serving tens of millions), underscoring the potential impact of tools that augment local diagnostic capacity. [3] [4]

Magnetic resonance imaging (MRI) is the imaging modality of choice for brain tumor detection and characterization due to its soft tissue contrast and multiparametric sequences. [5] Public repositories such as The Cancer Imaging Archive (TCIA) and the BraTS (Brain Tumor Segmentation) collections provide curated, annotated MRI datasets that underpin most contemporary deep-learning studies, enabling segmentation and classification research at scale. [6] [7]Several commonly used Kaggle and academic datasets (e.g., multi-class brain MRI collections) supplement institutional data and are frequently used for transfer learning and benchmarking. [8]

Preprocessing steps that materially affect model performance include standardizing image dimensions, intensity normalization, skull stripping or cropping, and augmentation (rotation, flipping, intensity perturbation) to increase effective dataset size and model robustness. [9] The Neuropredict pipeline documents resizing, normalization, augmentation, and an 80/20 (or similar) train/test split as standard practices used before training CNNs. [10]

Convolutional neural networks (CNNs) both custom architectures and transfer learning using pretrained backbones dominate current approaches to brain MRI classification. [11] Ensembles, feature extraction combined with classical classifiers, and hybrid segmentation-then-classification pipelines have each been proposed to improve robustness and interpretability. [12]Comparative studies and systematic reviews show that transfer learning often accelerates convergence and improves accuracy when labeled local data are limited, while segmentation tasks (BraTS) remain central for surgical planning and volumetric assessment. [7] [13]

Explainable AI (XAI) techniques Grad-CAM, saliency maps, layer-wise relevance propagation and others are widely adopted to highlight image regions that drive model decisions, which is crucial for clinician acceptance. [14] However, recent analyses question the consistency and clinical validity of some visualization methods in medical imaging and recommend rigorous evaluation of XAI outputs alongside quantitative metrics. [15] Measuring predictive uncertainty (e.g., using SoftMax confidence, Bayesian approximations, or ensemble variance) helps flag low-confidence cases that require human review. [16] Neuropredict is designed to report confidence scores with predictions and to incorporate explainability extensions (e.g., Grad-CAM) as part of ongoing development. [10]

External validation on site-specific hospital data is essential to estimate generalization. [17] Studies that report high internal accuracy but limited external testing often suffer performance degradation when applied to new scanners, sequences, or populations. [18] The Neuropredict project plans real-world testing on MRI scans (external to training data) to evaluate aggregate concordance and confidence scores; the project will ensure transparent result accounting and clarification where needed (e.g., differing summaries of correct predictions across sections). [10][19] Transparent reporting and reproducible test sets are needed to verify claims. [17]

Medical imaging models can inadvertently learn non-biological signals (scanner markers, demographics) that correlate with outcomes in training data, producing biased outputs across subgroups. [20] Work exposing models that predict protected attributes (e.g., race) from imaging has intensified calls for routine demographic auditing, balanced sampling, and fairness-aware evaluation prior to clinical use. [20][21] In low-resource settings, ensuring demographic and scanner diversity in training data is especially important to avoid harming under-represented populations. [21]

Deploying AI in clinical environments requires secure handling of imaging data (DICOM support, PACS integration), user authentication, and latency-aware APIs. [6][22] Practical deployments frequently leverage REST APIs (FastAPI/Flask) and lightweight frontends for clinician interaction; Neuropredict uses FastAPI and a web frontend with MySQL for metadata storage. [10] Before pilot rollout, cybersecurity, data governance, and local regulatory approvals must be obtained, and workflows must ensure clinicians retain final diagnostic authority. [23]

AI diagnostic aids can extend specialist reach, prioritize referrals, and reduce time to diagnosis when integrated with tele-radiology and task-shifting strategies. [24] To maximize impact in Tanzania and similar contexts, projects should partner with multiple hospitals to collect diverse, de-identified DICOM datasets; implement XAI and uncertainty reporting so clinicians can inspect and triage outputs; run prospective clinical pilots with outcome tracking; and publish transparent external validation results and code/data when permissible. [17][23] These steps align with recent systematic reviews that identify data diversity, explainability, and prospective validation as critical for clinical translation. [13]

3. PROBLEM STATEMENT

In Tanzania faces a severe shortage of radiologists and neurosurgeons, leading to delayed or missed brain cancer diagnoses. Many patients, especially in rural areas, lack access to timely and affordable diagnostic services.

Existing medical facilities are overwhelmed, and AI-driven diagnostic tools remain underutilized. As a result, late-stage detection increases mortality rates, and patients endure financial problems and hardships seeking specialized care.

Implementing an AI-powered MRI-based diagnostic tool can bridge this gap, improving early detection and treatment outcomes.

4. OBJECTIVES

4.1 Main Objective

To develop an AI-powered application that uses MRI scans to predict the possibility of brain cancer

4.2 Specific Objectives

a. To prepare datasets of MRI images for training and validation of the AI model.
b. To develop deep learning model, for tumor detection and classification.
c. To validate the AI web prediction application by comparing its diagnostic accuracy with traditional assessments

4.3 Figures and Tables

This section presents the key tables and figures summarizing the reviewed literature and the concept of structure of AI powered Brain Cancer prediction application.

Component	Description	Key Technologies/Methods	Benefits in Tanzanian Context	Reference
Clinical need and problem context	Brain cancer diagnosis in Tanzania is constrained by limited radiology and neurosurgery capacity, delayed referrals, and uneven access to advanced imaging. The reviewed work positions AI as a triage-support tool rather than a replacement for clinicians.	Needs assessment, healthcare workflow analysis, AI decision-support framing	Supports faster triage, better use of scarce specialists, and earlier referral from district and regional facilities.	
Data acquisition and preprocessing	The literature emphasizes MRI as the primary input, with public datasets such as TCIA and BraTS commonly used alongside any locally sourced, de-identified hospital images. Standard preprocessing improves robustness before model training.	MRI dataset curation, resizing, normalization, skull stripping/cropping, augmentation, train/test split	Improves model transferability across scanners and hospitals, which is important where imaging protocols and data quality vary.	[6], [7], [8], [9]
Modeling approach	Current studies favor CNN-based classification and transfer learning for brain MRI analysis.	CNNs, transfer learning, multiscale feature extraction, ensemble learning, hybrid segmentation-classification	Makes the system more practical for Tanzania by reducing dependence on very large local training datasets and improving diagnostic sensitivity.	

	Hybrid and multiscale designs are highlighted because they improve sensitivity to small			
Conceptual web application structure	Neuropredict is conceptualized as a full-stack web app: MRI upload on the frontend, FastAPI backend for inference, CNN model for classification, and database support for storing metadata and results. The interface should also display confidence and explanation outputs.	Web frontend, FastAPI REST API, CNN inference engine, MySQL metadata store, Grad-CAM, uncertainty estimation	Enables near real-time access in low-resource settings, supports clinician review, and creates a usable pathway for deployment in Tanzanian hospitals.	[10], [22], [23], [24], [25], [28], [31], [32]

5. ACKNOWLEDGMENT

We would like to express our sincere gratitude to all those who contributed to the successful completion of this review paper titled "AI-Powered Web-Based Application for Brain Tumor Detection."

First and foremost, we extend our deepest appreciation to our supervisor **Lusekelo Kibona**, for his invaluable guidance, continuous support, and constructive criticism throughout the development of this work. Their expertise in the field and dedication to academic excellence greatly influenced the quality and direction of this study.

We also wish to acknowledge **Ruaha Catholic University** for providing a conducive learning environment and access to academic resources that made this review possible. Our sincere thanks go to our lecturers and academic staff for equipping us with the theoretical and practical knowledge necessary to undertake this research.

We are grateful to the various researchers and authors whose scholarly works on artificial intelligence, medical imaging, and brain tumor detection formed the foundation of this review. Their contributions to the field have been instrumental in shaping our understanding of the subject.

Special appreciation goes to our fellow students and colleagues for their encouragement, collaboration, and valuable discussions that enriched this work.

Finally, we extend our heartfelt thanks to our families and friends for their unwavering support, patience, and motivation throughout the entire research process.

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International Journal of Engineering and Information Systems (IJEAIS)
ISSN: 2643-640X
Vol. 3 Issue 7, march – 2026, Pages: 1-1

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