

RUAHA CATHOLIC UNIVERSITY (RUCU)



FACULTY OF INFORMATION AND COMMUNICATION TECHNOLOGY
DEPARTMENT OF COMPUTER SCIENCE
AI-POWERED BRAIN CANCER PREDICTION APPLICATION

SUBMITTED BY:

S/N	NAME OF THE STUDENT	REGISTRATION NUMBER
01	MAHMUDU JUMA MCHA	RU/BSCSE/2023/058
02	LUQMAN KHALFANI MWAKIOJA	RU/BSCSE/2023/085
03	JOSEPH LUCAS PETRO	RU/BCS/2023/087
04	DEONISIUS FAIDA FRENKIUS	RU/BSCSE/2024/091
05	DEBORA MESHACK NJOTTO	RU/BCS/2024/211
06	EDSON MAKUNGA JACKOBO	RU/BCS/2024/313
07	DAVINA SAIMONI MWANDELA	RU/BCS/2024/165

SUPERVISOR: LUSEKELO KIBONA

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CHAPTER ONE

INTRODUCTION

1.0 Background of the Study

Brain cancer, also referred to as brain tumors or central nervous system (CNS) malignancies, represents a significant global health challenge due to its high morbidity and mortality rates. Globally, brain tumors account for approximately 1.6% of new cancer cases and 2.5% of cancer-specific deaths, with over 308,000 new diagnoses and 251,000 deaths reported annually. [1]. In Africa, the incidence of brain cancer has seen a 13.9% increase in age-standardized rates between 1990 and 2016, highlighting a growing burden in resource-limited settings [2] [3]. In Tanzania specifically, primary brain tumors are relatively rare but still impactful, comprising around 3% of all cancer cases annually based on hospital data. According to recent estimates, Tanzania recorded 194 new cases of brain and CNS cancers in 2022, with a 5-year prevalence of 496 cases, underscoring the need for improved diagnostic tools in a country where healthcare access is often limited [4] [5] [6]. These tumors can be benign or malignant, with malignant types like gliomas and meningiomas often requiring early intervention for better outcomes [7].

The advent of artificial intelligence (AI) in medical imaging has revolutionized diagnostic processes, particularly through the analysis of magnetic resonance imaging (MRI) scans. AI techniques, such as deep learning models, enable automated detection and classification of brain tumors with high accuracy, addressing limitations in manual interpretation by radiologists [8]. For instance, convolutional neural networks (CNNs) have been employed to segment and classify tumors, improving early detection rates and reducing diagnostic errors [9] [10] [11]. This project aims to leverage AI to develop an application tailored for brain cancer prediction, focusing on MRI data to support healthcare in Tanzania, where specialized radiological expertise is scarce.

1.1 Problem Statement

Brain cancer diagnosis in Tanzania is hindered by late detection, limited access to advanced imaging facilities, and reliance on manual MRI interpretation, which is prone to human error and variability [4] [12]. With only a small fraction of cancers (around 3%) being brain-related,

yet contributing to significant mortality (e.g., 163 deaths in 2022), the lack of efficient, accessible tools exacerbates delays in treatment [4] [6]. Traditional methods often miss subtle tumor features, leading to misdiagnosis or delayed intervention [13] [14] . In low-resource settings like Iringa, Tanzania, the shortage of the service and trained specialists further compounds these issues, resulting in poorer patient outcomes and increased healthcare costs [12] [15].

1.2 Objectives of the Project

1.2.1 Main Objective

To develop an AI-powered application for predicting brain cancer from MRI images to predict the possibility of brain cancer

1.2.2 Specific Objectives

1. To collect and preprocess a dataset of MRI images for training and validation of the AI model.
2. To design and train deep learning models, for tumor detection, and classification.
3. To validate the AI system by comparing its diagnostic accuracy with traditional assessments

1.3 Significance of the Project

The success of this project will lead to:

1. Improved early detection of brain cancer, increasing survival rates.
2. Reduced burden on radiologists and neurosurgeons by providing AI-assisted diagnostics.
3. Enhanced accessibility to diagnostic services.
4. Advancement of medical research and AI implementation in Tanzania's healthcare system.

1.4 Scope of the Project

This project will cover the following areas.

- Analyzing the context of brain cancer diagnosis in Tanzania
- Data and requirement collection from publicly available datasets and locally sourced images for training, evaluations and development.
- Development of the model; It will employ deep learning techniques to analyze MRI scans and predict the possibility of having brain cancer.
- A user-friendly interface will be designed and developed for healthcare professionals to interact with the system seamlessly.
- The system's performance will be evaluated through comparative analysis with traditional diagnostic methods.
- The project will focus on enhancing diagnostic accuracy and efficiency but will not replace professional medical judgment.

1.5 Chapter Summary

This chapter provided an overview of brain cancer's background, the problem of delayed diagnosis in Tanzania, the project's objectives, its significance, and scope. It sets the foundation for reviewing existing literature and outlining the methodology in subsequent chapters.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

In the field of brain cancer detection, there has been significant progress in utilizing artificial intelligence (AI), specifically deep learning models, to improve the accuracy and efficiency of diagnosing brain tumors [16] [8]. Research has demonstrated the potential of AI to analyze brain MRI scans with high precision, assisting radiologists in identifying tumors that might be overlooked in traditional manual assessments [10] [11]. This capability is crucial because early detection significantly impacts the prognosis and treatment outcomes for patients, especially in cases of aggressive brain cancers [17]. The application of AI in healthcare offers the promise of reducing human error and alleviating the burden on healthcare professionals, providing a more efficient means of diagnosis [18].

Various studies have highlighted the effectiveness of deep learning models, such as convolutional neural networks (CNNs), in segmenting and classifying brain tumors from MRI images [16] [19]. These models are trained on large datasets, allowing them to learn complex patterns and make accurate predictions even in the presence of variability in tumor size, location, and type [20] [21]. While AI models show great promise, the integration of explainable AI (XAI) is also a key focus to ensure that the results are understandable and interpretable by healthcare professionals [22] [23]. This not only boosts the trust of clinicians in AI-generated results but also aligns with the broader goal of complementing rather than replacing the expertise of radiologists. Overall, the adoption of AI in brain cancer detection can significantly improve diagnostic workflows, reduce diagnostic time, and contribute to better patient outcomes.

2.2 Empirical Review

Empirical studies have underscored the transformative role of deep learning (DL) in brain tumor detection, classification, and segmentation from MRI images, often achieving high

accuracy while addressing clinical challenges such as variability in tumor appearance and limited data availability [24].

A systematic review by Islam et al. (2025) examined DL-driven interpretable models for brain tumor prediction, utilizing convolutional neural networks (CNNs) enhanced with explainable AI (XAI) techniques like SHAP for feature analysis, reporting classification accuracies up to 95.86% on public MRI datasets, with a focus on real-time clinical deployment and integration with large language models for diagnostic reporting. The reviewed CNN–XAI models depend on high-quality public MRI datasets, advanced computing resources, stable electricity, and reliable internet connectivity for real-time deployment and LLM integration, conditions that are largely unavailable in most Tanzanian healthcare facilities [25].

Similarly, Rudie et al. (2024) reviewed DL applications in neuro-oncology, highlighting segmentation tasks with models like U-Net and classification using CNNs for predicting mutation status in gliomas, achieving Dice scores above 0.85 for tumor core delineation and emphasizing the need for generalizable models in diverse patient populations. The emphasis on mutation prediction and highly annotated segmentation assumes access to molecular diagnostics and diverse, well-labeled datasets, which are rarely available in Tanzania, limiting clinical applicability [26].

In another study, Díaz-Pernas et al. (2021) proposed a multiscale CNN for brain tumor classification and segmentation, trained on augmented MRI data, yielding accuracies of 98.17% with Vision Transformers outperforming traditional CNNs, and incorporating XAI methods like Grad-CAM to validate focus on tumor regions. The use of multiscale CNNs and Vision Transformers requires high computational power and heavily augmented data, making the approach impractical for low-resource hospitals with limited hardware and small datasets [27].

Balwant (2025) conducted a systematic review on XAI in brain tumor detection, evaluating transfer learning models like ResNet and DenseNet, which achieved up to 97.71% accuracy

on MRI scans, but noted inconsistencies across optimizers and longer computation times for hybrid architectures. The reported inconsistencies across optimizers and long computation times for hybrid XAI models pose challenges for deployment and maintenance in environments with limited technical expertise and processing capacity [28].

Thakur et al. (2023) explored DL approaches including YOLO variants for tumor detection, reporting precision metrics over 0.90 and highlighting the benefits of transfer learning for multi-class classification of gliomas, meningiomas, and pituitary tumors. YOLO-based detection models require large labeled datasets and GPU acceleration, which restricts their feasibility in Tanzanian settings where labeled medical data and AI hardware are scarce [29].

Senan et al. (2025) reviewed hybrid ML-DL models for segmentation, achieving Dice coefficients of 0.959 for whole tumors on BraTS datasets through adversarial learning and attention mechanisms, though challenges in dataset diversity were identified. Although high segmentation accuracy is achieved, the reliance on adversarial learning and attention mechanisms introduces model complexity that is difficult to implement and sustain in resource-constrained healthcare systems [30].

2.3 Related works

From the literature, it discusses the challenges faced in implementing artificial intelligence (AI) in healthcare, particularly in low-resource settings such as rural areas. It emphasizes the lack of infrastructure, skilled professionals, and access to advanced technology in these regions. It highlights the potential of AI to bridge these gaps, offering solutions for faster, more efficient diagnoses that could be especially beneficial in settings like Tanzania, where there is a shortage of radiologists and healthcare professionals [18] [31].

The systematic review focuses on the application of AI in early brain tumor detection, particularly through the analysis of MRI scans. The authors discuss various AI methodologies, including convolutional neural networks (CNNs), which have shown promise in accurately identifying brain tumors. The paper also touches on the advantages of AI in improving diagnostic accuracy, which aligns with the goals of Neuropredict in providing rapid, reliable brain cancer detection, especially in areas with limited access to specialists [8] [10].

The work [31] provide an overview of recent advancements in deep learning for brain tumor classification and segmentation. The paper discusses the growing role of convolutional neural networks (CNNs) in medical imaging, particularly for brain tumor detection, which is a key aspect of Neuropredict's AI model. The authors also explore the benefits of deep learning in terms of reducing diagnostic time and increasing accuracy, which are essential in improving healthcare delivery in underserved regions [11].

2.5 Research Gap

While AI-driven systems for brain cancer detection have gained significant attention in recent years, there remains a notable gap in addressing the specific challenges faced in low-resource settings, such as those in Tanzania. Most AI-based systems for brain tumor detection, as discussed in the literature, focus on high-income countries where there is better access to advanced imaging technologies and healthcare infrastructure. [8], [18] These systems primarily target urban healthcare centers where radiologists and specialists are more prevalent. However, rural areas and developing nations, such as Tanzania, continue to face difficulties in accessing timely and accurate diagnostic services due to a shortage of resources, skilled personnel, and advanced technologies [32]

The existing AI solutions often lack customization for the unique needs of developing countries. For instance, many AI models are designed for specific types of MRI scans and may not perform equally well across different population groups or healthcare settings [33]. Additionally, there is insufficient integration of explainable AI in medical systems, especially for healthcare workers who may not have expertise in AI models. This limits clinicians' ability to trust AI predictions and effectively collaborate with AI systems [34] [35]. Neuropredict seeks to fill this gap by developing an AI-based tool that not only offers high accuracy in detecting brain tumors from MRI scans but also incorporates explainable AI features to provide clarity on the rationale behind its predictions

Another significant gap is the lack of AI systems designed specifically to assist

healthcare professionals in areas with a shortage of specialists. Although AI models like CNNs have shown high accuracy in brain tumor detection, their use is still limited in low-resource settings where they could have the most impact. Neuropredict aims to be a complementary tool for radiologists and healthcare professionals, helping them make faster, more informed decisions, particularly in rural and underserved areas. The integration of AI can reduce diagnostic time and increase accuracy, thus addressing both the availability of skilled professionals and the timely delivery of healthcare services in areas where these resources are scarce [36] [37].

2.6 Chapter Summary

This chapter reviewed empirical evidence and related AI works for brain tumor prediction, identifying gaps in accessibility and interpretability that this project aims to fill.

CHAPTER THREE

METHODOLOGY

3.1 Project Approach

The Neuropredict project adopts a **quantitative research approach**. This approach is appropriate because the project focuses on measurable, data-driven outcomes, such as accuracy, sensitivity, and specificity of the AI model in detecting brain cancer from MRI scans. The success of the system will be quantified through various performance metrics, including precision, recall, F1 score, and confusion matrix, which can be measured objectively. Additionally, data collection for training the model involves large datasets of labeled MRI scans, and the impact of the app will be evaluated by comparing diagnostic speed and accuracy with traditional methods.

3.2 Project Methods

The methodology for this project will follow the **CRISP-DM (Cross-Industry Standard Process for Data Mining)** framework, which provides a structured and iterative approach to solving data-driven problems. This model ensures that the project progresses systematically from understanding the objectives to deploying a robust solution.

The CRISP-DM methodology is iterative, meaning insights from one phase can lead to revisiting previous phases. For instance, poor evaluation results may require additional data preprocessing or adjustments in the model architecture.

Business Understanding

The primary objective of the Neuropredict project is to develop a predictive system that uses machine learning to identify the possibility of an individual having brain cancer or not from MRI scans.

The system must provide accurate predictions and deliver user-friendly interfaces for doctors.

Specific goals and constraints include, achieving high sensitivity and specificity for cancer predictions and providing a fast and accessible platform for users via web app.

Data Understanding

The data for the Neuropredict project will be obtained from publicly available MRI datasets, such as **The Cancer Imaging Archive (TCIA)** and **Kaggle datasets**.

This phase aims at identifying key characteristics, potential issues and patterns. Tools that will be used in this phase includes JupyterLab and python libraries that is, Pandas, Matplotlib and SeaBorn.

Key activities include:

- i. **Data Collection and Exploration:** Visualizing MRI scans to understand distribution, variations, and anomalies.
- ii. **Data Quality Assessment:** Identifying missing data, noise, or inconsistent formats.
- iii. **Labeling** : Ensuring proper categorization of MRI scans for training (e.g., labeled as "yes" or "no").

Data Preparation

The data preparation phase focuses on transforming raw data into a format suitable for machine learning. The tools to use in this phase includes TensorFlow, OpenCV, and Python scripts for automation. Preprocessing steps include:

- i. **Image Resizing:** Standardizing the resolution of MRI images to fit the input size of the model.
- ii. **Normalization:** Scaling pixel intensity values to a range (e.g., 0–1) to ensure uniformity.
- iii. **Data Augmentation:** Generating new training samples by applying transformations (e.g., rotation, flipping, zooming) to improve model generalization.
- iv. **Splitting Data:** Dividing the dataset into training, validation, and test sets
- v. Noise filtering

Modeling

This phase involves designing, training, and validating the predictive model. Tools to use in this phase includes TensorFlow, Keras, and Jupyter Notebook. A **Convolutional Neural Network (CNN)** will be used due to its effectiveness in image classification tasks.

Key steps includes the following:

- i. **Model Selection:** Experimenting with pre-trained models for transfer learning and custom architecture.
- ii. **Training:** Feeding labeled MRI scans into the model to learn patterns associated with brain cancer.
- iii. **Hyperparameter Tuning:** Optimizing learning rates, batch sizes, and layers to achieve high accuracy.

Evaluation

The model's performance will be evaluated using the test dataset to ensure it meets the project's success criteria.

- i. **Quantitative Evaluation:** Metrics like accuracy, recall(sensitivity), precision and confidence scores will be analyzed to measure predictive performance.
- ii. **Error Analysis:** Reviewing misclassified scans to identify patterns and improve model robustness.

Deployment

In the final phase, the trained model will be deployed as a fully functional system accessible to end-users. Deployment steps include:

- i. **Backend Development:** Implementing a REST API using **FastAPI** or **Flask** to handle image uploads and predictions.
- ii. **Frontend Development:** Designing responsive interfaces using **React**

3.3 Area of the Study

The Neuropredict app focuses on addressing the critical healthcare challenges in Tanzania, particularly in underserved rural areas where access to advanced diagnostic tools like MRI scans is limited. In such regions, there is a shortage of specialized healthcare professionals, such as radiologists, and diagnostic delays often result in late-stage cancer detection. By leveraging AI to analyze MRI scans and providing an accessible, affordable tool for early brain cancer detection, the app aims to fill this gap, especially in areas with limited access to healthcare resources. This solution is vital in a country like Tanzania, where healthcare resources remains a challenge, and it has the potential to be scaled to other parts. With integration into existing healthcare systems, Neuropredict can empower general healthcare practitioners with a reliable, AI-assisted diagnostic tool that complements the expertise of medical specialists and improves overall healthcare delivery [36]

3.4 Ethical Considerations

This study will adhere to ethical approval and dataset usage terms will be respected since public datasets will be used. All medical images will be anonymized to protect participant privacy and stored securely. The developed system is intended solely for academic purposes and will not replace professional medical diagnosis.

3.5 Project Timeline

The project will be conducted following timeline below.

Phase	Weeks	Deliverables
Project Planning and Proposal	1-2	Proposal document, tools list
Literature Review	3-5	Review report, references on algorithms and datasets

Data Collection and Processing	6-8	Collected dataset, cleaned and labeled data
Model Development	9-12	Trained models
Web Frontend Development	13-16	UI prototype
Backend and Integration	17-19	Model + API + app integration
Testing and Evaluation	20-21	Test reports and performance results
Final Report Writing	22-23	Full write-up

3.6 Project Budget

Project budget

Objective	Estimated cost(TZS)	Notes
Laptop	1,200,000/=	Good for ML training and system development
Storage device	25,000/=	Backups
Internet	50,000/=	Ensuring secure internet connection
Printing and binding	25,000/=	Final Report
Transport and Misc	50,000 – 150,000/=	Meetings and research conducting etc.

3.7 Chapter Summary

This chapter outlines the methodological framework adopted for the Neuropredict project, which aims to develop an AI-based system for brain cancer detection from MRI scans in the Tanzanian healthcare context. A quantitative research approach is employed to ensure objective evaluation through measurable performance metrics such as accuracy, precision, recall, F1-score, sensitivity, specificity, and confusion matrices. The effectiveness of the system is assessed by comparing diagnostic accuracy and speed against traditional diagnostic approaches.

The project follows the CRISP-DM methodology, providing a structured and iterative process that guides the project from problem understanding to system deployment. Publicly available MRI datasets from sources such as TCIA and Kaggle are used, with data exploration and preprocessing carried out using Python-based tools. Data preparation includes image resizing, normalization, augmentation, noise filtering, and dataset splitting to enhance model generalization and robustness.

A Convolutional Neural Network (CNN), combined with transfer learning techniques, is used for model development due to its suitability for medical image classification. Model performance is evaluated quantitatively and through error analysis to improve reliability. The trained model is then deployed as a web-based application using a RESTful API and a React frontend to ensure accessibility.

The study focuses on Tanzania, particularly underserved rural areas where shortages of radiologists and diagnostic delays are common. Ethical considerations are addressed through the use of anonymized public datasets and adherence to dataset usage policies, with the system intended strictly as a decision-support tool. Finally, a structured project timeline spanning planning, development, testing, and reporting ensures systematic project execution.

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