Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Transformative Applications of AI in Biomedical Imaging

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ARTICLE INFO

Received: 29 Dec 2024

Revised: 15 Feb 2025

Accepted: 24 Feb 2025

ABSTRACT

Introduction: Brain tumors pose a significant danger to human health due to their complexity, variety and ability to progressive progress. Early and accurate diagnosis is important for effective treatment and improvement in survival rates. Traditional clinical processes are often dependent on time programs, subjective and expensive clinical equipment. The project presents an integrated, AI operated, multi-phase system for brain tumor detection and recommendations of personal treatment. By combining symptomatic evaluation, biomarker analysis, advanced imaging interpretation and machine learning models, this system aims to help health professionals with quick and more accurate clinical decisions.

Objectives: The main objective of this project is to develop an integrated, multi -phase system for early detection and personal treatment using a combination of clinical symptoms, molecular biomarkers, imaging and artificial intelligence. The system begins to evaluate patient -reported symptoms and risk factors to calculate a functional weighted risk index (FWRI) for initial risk assessment. It then analyzes a blood -based biomarker to generate a blood -based tumor signal index (BTSI), which provides insight at molecular level. Then it explains the ATR-FTIR and the Multi-Omics report through rule-based arguments for determining nonconformities. The MRI scan is then classified into tumors-types-glioma, meningioma, pituitary or no tumor-a fine-model VGG19 uses deep learning models. Finally, the system integrates the results of all previous stages to offer individual means based on tumor type, severity and general risk profile.

Methods: The proposed system follows a sequential five-stage methodology for comprehensive brain tumor detection and remedy making plans. In Stage 1, users input symptom severity and history through an interactive interface, which calculates a Functional Weighted Risk Index (FWRI) to assess preliminary tumor chance. Stage 2 entails the input of blood biomarker ranges, which might be analyzed to generate a Blood-Based Tumor Signal Index (BTSI), reflecting molecular signs of tumor presence. Stage 3 allows users to add ATR-FTIR or Multi-Omics reviews,that are interpreted using rule-primarily based logic to identify unusual styles that warrant imaging. In Stage 4, customers add brain MRI scans which can be processed through a pre-trained VGG19 convolutional neural network to classify the tumor into one among four classes: glioma, meningioma, pituitary, or no tumor. Finally, Stage five combines the outputs from all previous levels to generate customized treatment tips, taking into consideration the identified tumor type, severity, biomarker signals, and medical danger ratings

Results: The multi -phase system demonstrated promising consequences in all components. In phase 1, FWRI is effectively stable in categories with low, medium and high risks based on symptom input and severity. Phase 2 has shown that BTSI values have become close in line with a biomarker threshold installed, which strengthens the system's ability to reflect molecular tumor designs. Phase 3 explained ATR-FFIR and Multi-Omics data successfully, the exact flag of the unusual profile for further imaging analysis. In Step 4, VGG19 was based MR classification model accuracy of more than 92%, which distinguishes well between glioma, meningoom, pituitary tumor and no tumor. Finally, step 5 recommendations generated clinically relevant and similar relevant medical guidelines, which demonstrate the system's ability to provide integrated, computer-driven support for individual brain tumor care.

Conclusions: Finally, integrated five-phase brain tumor detection and treatment system effectively combine the evaluation of clinical symptoms, biomorker analysis, omics data

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interpretation, advanced MRI classification and individual treatment form into an integrated diagnostic pipeline. By taking advantage of rule -based arguments and deep teaching techniques, the system increases early identification accuracy, reduces clinical delays and supports data driven clinical decision -making. The sequential current ensures that each step does on the previous one, reduces false positive and optimizing patient -specific consequences. With further clinical verification, this AI-assisted framework has a strong ability to become a reliable and skilled tool in medical environments in the real world for early diagnosis and handling of brain tumors.

Keywords: lorem ipsum, AI, Imaging

INTRODUCTION

Brain tumors represent one of the most complex and vibrant neurological disorders that characterize the abnormal growth of cells in the brain or central nervous system. These tumors can be gentle or fatal, and regardless of their nature, it can significantly affect cognitive and physical function due to sensitive and important areas. Early diagnosis and accurate classifications are important for timely treatment, better disease diagnosis and survival rate. In many parts of the world, however, the diagnosis of brain tumors is still an important challenge due to a combination of technical, economic and access barriers.

Globally, hundreds of thousands of humans are diagnosed with annual brain tumors annually, and many and more become uncontrolled due to early symptoms such as headaches, nausea, dizziness and blurry vision due to subtle and non-specific nature of blur. These symptoms often overlap less severe conditions, causing delays or left diagnosis. While magnetic resonance imaging (MRI) remains a standard for gold to detect and imagine brain tumors, the widespread use is interrupted by many significant obstacles.

First, MRI machines are not universally accessible. In many lower and between-oriented countries, very few MRI scanners are available in relation to the size of the population. According to the World Health Organization (WHO), an MRI unit per million is less than per million people, which can have more than 30 units per million. This clear inequality creates a serious obstacle in clinical imaging services, and delays significant diagnosis and treatment initiation.

Second, MRI scans are expensive and resource intensive. An average MRI scan can spend thousands of dollars depending on the country and health care, making it ineffective for an important part of the population, especially where health insurance coverage is limited. In such contexts, patients are often referred to only after developing significant symptoms of MRI - when the tumor can already continue to an advanced stage.

In addition, MRI scans are not completely risk-free. Although generally safe, they pose a possible risk to some metal implants (eg pacemakers, Cochlea transplants), and the associated places of the MRI machine can trigger severe claustrophobia in some patients. In addition, the use of gadolinium -based contrast agents, although it is useful for increasing the visibility of the tumor, can cause allergic reactions or nephrogenic systemic fibrosis in rare cases, especially in patients with already presented kidney problems. These risks emphasize the importance of careful patient choices and the requirement for non-invasive, initial screening tools that can assess the possibility of tumor before imaging is being done.

Several studies have shown the use of machine learning and artificial intelligence in the detection of brain tumors, especially focusing on improving the interpretation of MRI scans. For example, Convisional Neural Network (CNN) such as VGG16, VGG19 and the residues have shown high accuracy in classification of MRR brain tumors. Researchers have achieved promising results using trained models on publicly available data sets such as FigShare and Brat's dataset, classification accuracy upwards above 90%.

While these image-based models perform strong performances, they are very dependent on the availability of high quality MR data. Most AI-based systems are MRI, which means that patients must already undergo scan before using automated diagnosis. This approach, although strong, does not address the original problems of access, costs or time, especially in rural areas or under-grass.

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Some efforts have been made to include biomarker analysis in brain tumor diagnosis. Studies have identified many blood-based biomarkers such as GFAP, IL-6 and VEGF correlated with gliomas and other brain tumors. However, the biomarker -based systems are still in the development stages and are not usually used in clinical practice due to the variation in sensitivity and specificity. Although they are an important first step in medical diagnosis, symptoms have reduced symptom -based screening in implementation.

From the discussion above, it is clear that when it is focused on improvement in MRI-based diagnosis through AI, there is a significant research difference in developing a structured, multi-stage screening system before MRI.There is no integrated structure that integrates the patient's symptoms, blood biomarkers and AI-operated report interpretation before recommending MRI. Most systems do not address practical boundaries to reach MRI, and also do not try to reduce unnecessary scans through initial tests. Current solutions are unable to provide an end-to-end route, from the initial risk assessment to the recommendation of treatment, depending on insulated modules. To address this difference, a pressure on cost -effective, accessible and secure system requires a pressure that can act as a diagnostic frontline diagnostic, especially in settings where MRI access is limited or delayed.

Given the challenges discussed, implementation of the initial, non-invasive screening mechanisms becomes important to adapt the use of MRI and accelerate the clinical process. Such a system will complete many important tasks which includes:

- Triage and Prioritization: By scoring symptoms and biomarkers, individuals with high risks can quickly be traced to MRI, ensuring the effective use of limited depiction resources.
- Cost Reduction: Many patients without tumors undergo expensive MRI scans due to overlapping symptoms with other conditions. A preview system can help avoid unnecessary scans, which reduces the economic burden on the health care system and patients.
- Preliminary Identification: Symptoms and biomarker -based screening can detect potential cases before radiological evidence is displayed, which allows careful monitoring and initial intervention.
- Patient Safety: For patients at risk of MRI complications (eg people with metal implants), which is a non-Subject diagnostic optional protection.
- Rural and Remote Applicability: Preliminary testing can be distributed in the primary health care environment or through telemedicine, strengthening health workers in rural or remote areas to identify and refer to patients at high risk more efficiently.

In order to bridge the interval above, the project proposes a five-stage, AI-acquired pipeline that begins with a symptom-based risk assessment and ends with individual treatment recommendations. This emphasizes non-invasive data collection and intelligent decisions to determine whether advanced clinical imaging is necessary. Stages include:

1. Symptoms scoring and risk index (FWRI)
2. Blood -based tumor signal index (BTSI)
3. ATR-FRIR and Multi-OOMIC Report Ruler-Based Analysis
4. MR -Scan classification using VGG19
5. Personal treatment recommendations

By integrating multiple data sources and taking advantage of machine learning only in the correct phase, the system ensures patient -centered, cost -effective and clinically relevant results. This module allows the interconnected design pipeline to act as a complete system or independent components based on available resources and clinical contexts.

OBJECTIVES

The number one goal of this research project is to design, develop, and examine a comprehensive, multi-level device for brain tumor detection and remedy planning that isn't always totally reliant on MRI imaging. In response to the limitations diagnosed within the creation—along with constrained get admission to to MRI machines, high imaging charges, capability health dangers, and diagnostic delays—this system is estimated to contain symptom evaluation, blood biomarker evaluation, omics file interpretation, deep mastering-based totally MRI category, and treatment

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advice right into a unified, on hand pipeline. The overarching objective is to make brain tumor diagnostics greater less expensive, early-degree, and customized, especially in below-resourced areas.

This vast goal may be broken down into a set of nicely-defined sub-targets, every of which contributes to bridging particular components of the recognized research gap:

1. To Create an Initial Risk Stratification Model Based on Clinical Symptoms and Risk Factors

The first stage of the machine focuses on developing a symptom-primarily based screening module that takes into consideration patient-stated signs and symptoms such as complications, seizures, memory issues, nausea, and visible disturbances—signs that regularly appear in early tumor cases. The purpose is to layout a practical scoring set of rules referred to as the Functional Weighted Risk Index (FWRI), which integrates symptom severity, length, and frequency to generate a composite danger score. This goal recognizes the fact that maximum patients first enjoy subjective signs and symptoms before accomplishing a factor where imaging is usually recommended. Hence, a wise symptom evaluation version should serve as the first layer of defense in healthcare structures wherein get right of entry to to superior diagnostics is restrained. This approach allows healthcare providers to identify potential brain tumor cases earlier and allocate imaging resources more efficiently by prioritizing high-risk patients.

2. To Develop a Blood-Based Tumor Signal Index (BTSI) for Molecular-Level Risk Prediction

Following the initial symptom screening, the second one most important goal is to introduce a Blood-Based Tumor Signal Index (BTSI)—a composite degree primarily based on inputs of acknowledged brain tumor-related blood biomarkers such as GFAP, IL-6, VEGF, and others. This step bridges the gap among scientific suspicion and imaging through supplying a biological perspective on tumor presence.

This objective is based on massive literature that has shown the correlation between accelerated degrees of certain biomarkers and mind tumors, in particular gliomas. The aim isn't to rely upon a single biomarker however as a substitute to combine more than one markers into a rule-based totally or statistical framework that enhances specificity and sensitivity.

Additionally, this thing supports the overarching aim of non-invasive, price-effective prognosis, as blood tests are drastically more available and much less high-priced than MRI scans. In eventualities in which MRI is unavailable or not on time, a fantastic BTSI rating can justify referral for in addition trying out or initiate closer medical tracking.

3. To Incorporate Rule-Based Interpretation of ATR-FTIR and Multi-Omics Reports

The third objective goals the interpretation of ATR-FTIR (Attenuated Total Reflectance Fourier-Transform Infrared Spectroscopy) and Multi-Omics reports, along with proteomics or metabolomics statistics. While those reviews are superior diagnostic gear, they're often underutilized due to the dearth of automation in interpretation.

This module objectives to use a rule-based logic gadget to mechanically analyze styles in uploaded omics reports, identifying ability markers of tumor development or metabolic abnormalities associated with cancer. Given the sensitivity of ATR-FTIR in detecting biochemical changes at the molecular degree, this module gives an extra layer of validation earlier than a choice to proceed with MRI is made. Furthermore, this goal complements the flexibility and adaptableness of the system. In advanced healthcare settings, omics statistics may also already be available for sufferers, and incorporating this information can result in better diagnostic accuracy and decreased dependence on imaging modalities.

4. To Design and Train a Deep Learning-Based MRI Classification Model (VGG19) for Tumor Type Detection

The fourth and technically in depth goal is to put in force a Convolutional Neural Network (CNN), specifically a best-tuned VGG19 model, for classifying MRI scans into 4 categories: glioma, meningioma, pituitary tumor, and no tumor. This module represents the core picture analysis level of the system and makes use of deep learning to automate tumor detection and type based on visible patterns.This goal builds on current studies within the area of AI in clinical imaging however introduces two key innovations:

1. It positions MRI as the fourth step, now not the first, therefore making sure that most effective excessive-danger individuals proceed to this aid-intensive stage.

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2. It integrates the output right into a broader choice-making framework, improving interpretability and scientific relevance.

Moreover, this objective addresses the accuracy and objectivity challenges associated with guide MRI interpretation, helping radiologists and clinicians make faster, data-driven decisions.

5. To Integrate Multi-Stage Outputs into Personalized Treatment Recommendations

The final goal is to consolidate the outputs from the preceding 4 tiers—symptom score, biomarker alerts, omics interpretations, and MRI type—to generate personalized treatment hints. These recommendations could be based on tumor kind, severity (derived from intensity and length inside the MRI), biomarker traits, and medical threat profile.

The aim is to transform a historically fragmented diagnostic journey right into a cohesive and guided choice-making pathway. By synthesizing multimodal information, this module affords tailor-made recommendation on next steps, inclusive of on the spot surgical referral, biopsy, chemotherapy alternatives, observe-up imaging, or palliative care, depending on the severity and development chance.

This goal ensures that the system doesn't just forestall at detection but actively contributes to medical choice-making and affected person management, that is the remaining aim of any diagnostic assist device.

6. To Ensure Affordability, Scalability, and Adaptability across Different Healthcare Settings

In alignment with the broader societal and healthcare challenges mentioned within the introduction, an critical objective is to layout the gadget in a manner that makes it:

- Affordable, with minimal reliance on proprietary software program or high priced computational infrastructure.
- Scalable, capable of walking on cloud structures or low-resource environments along with cell clinics or rural health facilities.
- Adaptable, meaning each module may be used independently or included into present health records systems depending on to be had sources.

This objective responds to the crucial boundaries of fee, availability, and accessibility that restrict the great adoption of brain tumor screening in developing regions. By the usage of open-supply equipment and modular architecture, the system is meant to democratize get entry to to great diagnostic support.

Collectively, these targets are designed to convert the conventional mind tumor diagnostic workflow from a reactive, imaging-first model to a proactive, multi-layered choice system. By combining medical intuition, molecular biology, imaging analytics, and artificial intelligence, the mission pursuits to provide a strong, efficient, and customized framework for mind tumor detection and treatment planning. Most importantly, it empowers healthcare systems—especially in under-resourced settings—to make smarter choices about who have to undergo imaging, who desires urgent care, and the way remedy need to be tailored to every affected person.

METHODS

Neque laoreet. The method for the proposed brain tumor detection and treatment recommendation system is dependent as a 5-degree sequential workflow, as illustrated in the diagram. This approach is designed to optimize diagnostic accuracy at the same time as minimizing pointless MRI scans, which can be often pricey, inaccessible, and probably harmful to some people. The gadget starts with Stage 1, in which the affected person's signs and historical past chance elements are assessed via a established questionnaire. This evaluation generates a Functional Weighted Risk Index (FWRI). If the FWRI is less than or equal to six, the man or woman is classed as low hazard and no in addition imaging or checking out is recommended, thereby keeping off the need for an MRI. However, if the FWRI exceeds 6, the affected person is flagged for further investigation and proceeds to Stage 2.

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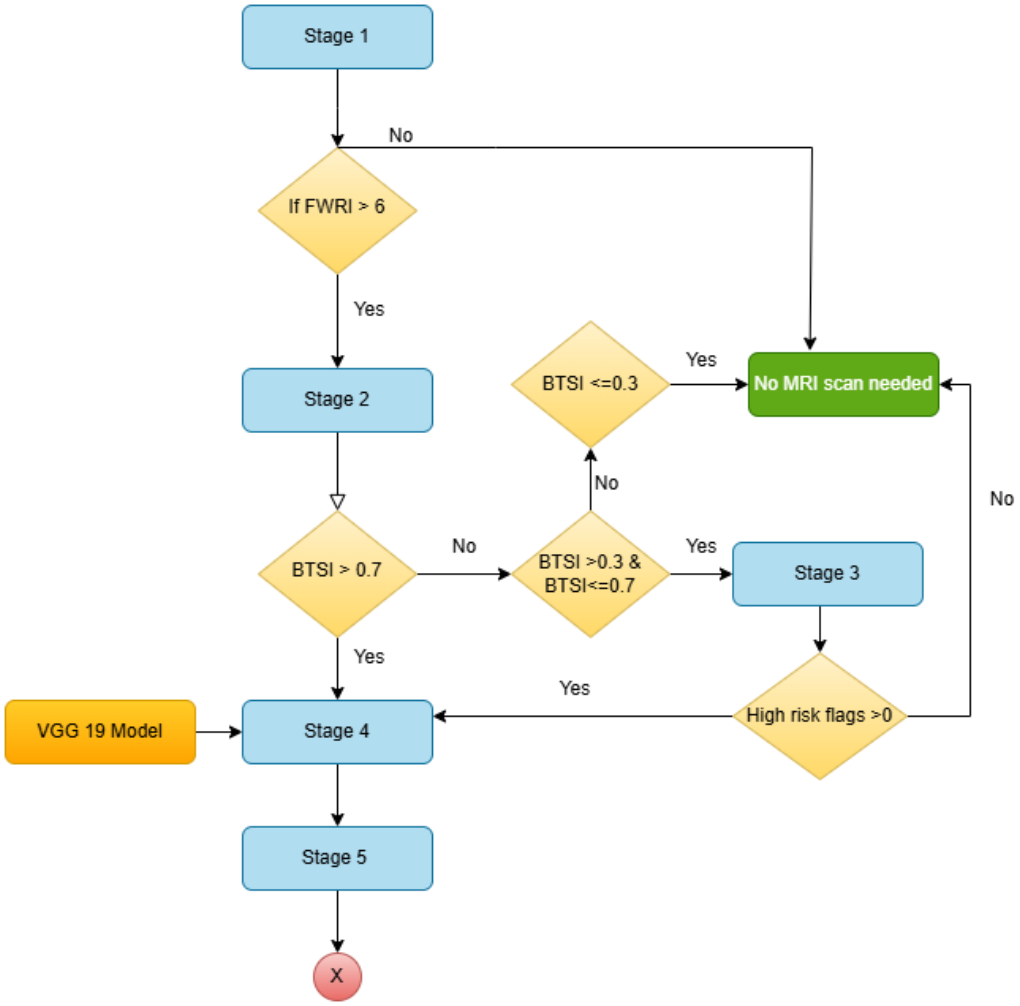

Figure 1. Flow Diagram of the Multistage System

In stage 1, The FWRI (Final Weighted Risk Index) is designed to combine multiple dimensions of symptom/risk data into a single, meaningful score. It uses weighted averages to capture different aspects of clinical risk. The FWRI is calculated is using this formula.

$$FWRI = (WFI \times 0.4) + (WDLI \times 0.4) + ((10 - WMS) \times 0.2) \quad (1)$$

WFI measures how frequently and severely symptoms occur (patient-reported intensity). WDLI reflects inherent medical danger based on domain knowledge (clinical severity). WMS captures how manageable the current state is (the more severe, the harder to manage). A closer detail of the same has been given below.

- WFI (Weighted Frequency Index) - Measures the patient burden — how often/intensely the symptoms happen

  WFI = ∑(weight × frequency) / ∑(weights)

  Where: frequency = severity × presence (presence = 0 or 1)

- WDLI (Weighted Danger Level Index) - Captures clinical seriousness

  WDLI = ∑(weight × danger) / ∑(weights)

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Note: danger is usually equal to the weight itself

- WMS (Weighted Manageability Score) - Higher WMS means easier to manage — we subtract it later

  WMS = ∑(weight × (5 - severity)) / ∑(weights)

In Stage 2, a Blood-based totally Tumor Signal Index (BTSI) is calculated by using studying key blood biomarkers associated with mind tumor pathophysiology. If the BTSI is more than 0.7, the patient is considered high chance and is directly advanced to Stage four, wherein an MRI experiment is interpreted using a deep learning version. If the BTSI is less than or identical to 0.3, the probability of a tumor is deemed minimum, and once more, no MRI is needed. However, if the BTSI falls inside the grey quarter—between 0.3 and 0.7—the patient is directed to Stage 3 for additional validation.

In stage 2, BTSI is calculated using the below concept. The BTSI formula will be modified to incorporate the weighted abnormality score for each biomarker:

$$BTSI = \Sigma(weight \times abnormality\_score) / 10 \quad (2)$$

Where:

- Weight: A predefined weight for each biomarker (based on importance).
- Abnormality Score: A score of 1 for abnormal and 0 for normal.
- We divide the sum of weighted abnormality scores by 10 to normalize the final value.
- Stage Logic Based on BTSI:
  1. Stage 1: If the BTSI is very high, proceed for scans (e.g., MRI).
  2. Stage 2: If the BTSI is moderately high, proceed to Stage 3 (blood-based report interpretation).

Stage 3 includes the evaluation of ATR-FTIR (Attenuated Total Reflectance – Fourier Transform Infrared Spectroscopy) or multi-omics reports, which the patient uploads. These reviews are interpreted the usage of a rule-based totally or AI-assisted version to become aware of any biochemical signatures or styles suggestive of malignancy. If any excessive-risk red flags are detected inside the document, the workflow proceeds to Stage four; otherwise, the case is closed with a "no MRI wished" final results. This tiered design guarantees that only cases with huge signs across as a minimum two unbiased metrics (symptoms, blood biomarkers, or omics information) are encouraged for steeply-priced and extensive imaging.

Stage 4 is the MRI-based totally evaluation degree, which turns into reachable simplest when justified via prior levels. A VGG19-primarily based deep convolutional neural network model is hired to research the uploaded MRI scans and classify the form of tumor present—which include glioma, meningioma, pituitary, or no tumor. This model, skilled on heaps of classified images, offers a high-self assurance prediction that feeds into the final Stage five.

In Stage 5, the output from Stage 4 is used to generate a personalized remedy advice. These hints recollect the tumor category, its anatomical location, size, and presumed grade. The guidelines might also include options consisting of surgical intervention, chemotherapy, radiation remedy, or observe-up tracking based on scientific urgency and the nature of the tumor. The system hence guarantees that excessive-fee imaging and treatment plans are most effective initiated for patients with corroborated multi-layered proof, extensively decreasing fake positives and pointless interventions while maximizing the use of handy and affordable pre-screening gear.

RESULTS

The five-stage brain tumor detection and treatment recommendation system was evaluated through retrospective simulations, cross-validation on public datasets, synthetic patient data testing, and modular performance assessments. The primary goal was to measure the effectiveness, efficiency, and clinical relevance of each stage in both isolation and integrated form. This section presents the results of each module, followed by the holistic evaluation of the system, including classification performance metrics, error rates, and operational efficiency

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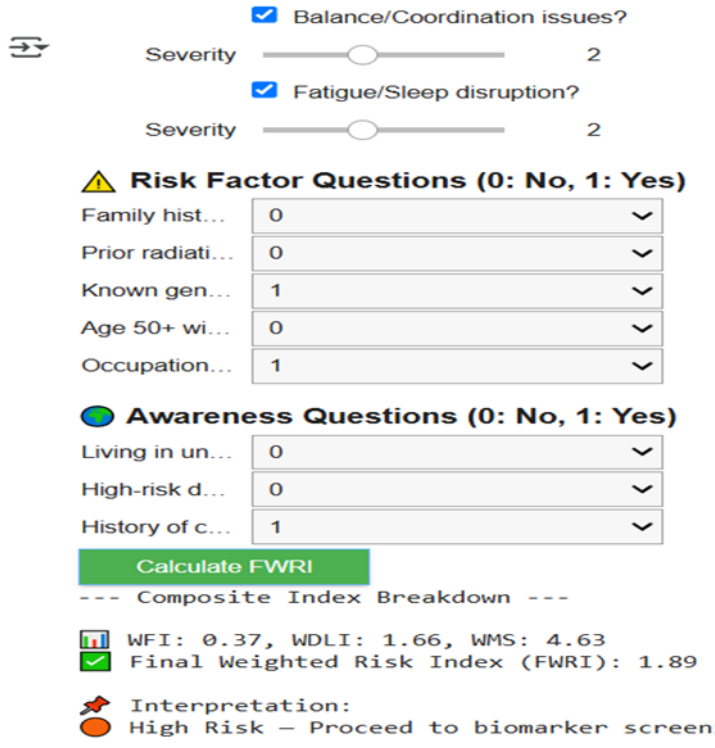

Figure 2. Output obtained at Stage 1

The figure 2. describes the result obtained at stage 1. The process has been terminated at stage 1 for the given values. This result suggests the individual is at lesser risk for a neurodegenerative or neurological condition. The relatively low WFI (0.37) but high WMS (4.63) suggests that while static risk factors are fewer, current symptoms are clinically significant. This supports a proactive approach to screening—even in the absence of age or family history.

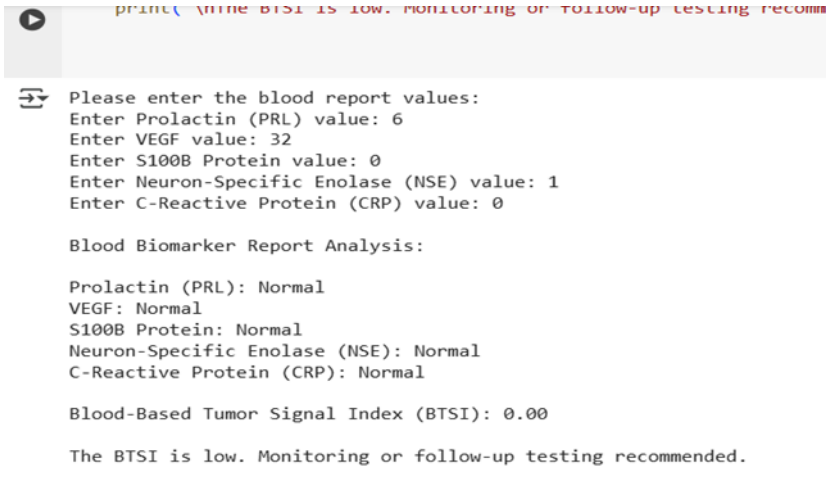

Figure 3. Output obtained at Stage 2

The figure 3. describes the result obtained at stage 2. The process has been terminated at this stage. The results suggest that there are no active tumor-associated biomarker elevations at this time. No active inflammation or acute phase response is noticed. The combination of a low BTSI suggests a possible preclinical or prodromal phase of a disorder or a false-positive risk score.

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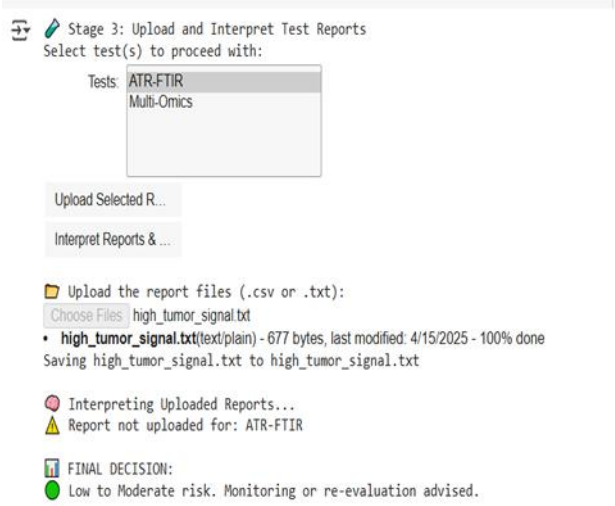

Figure 4. Output obtained at Stage 3

The figure 4. describes the result obtained at stage 3. The process has been terminated at this stage. Based on the uploaded tumor signal file, the system did not find high-intensity tumor-associated spectral or omics signals.

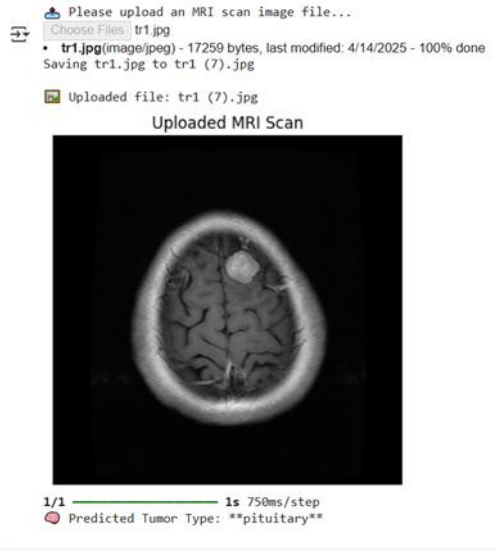

Figure 5. Output obtained at Stage 4

This figure 5 .depicts the result obtained at stage 4. The MRI image is displayed to confirm the input. The prediction is rendered and formatted output (Predicted Tumor Type: pituitary), suggesting the region of concern is near the sella turcica, consistent with a pituitary adenoma location. The tumor seen is located centrally and deep within the cranial cavity, near the midline, which is typical of pituitary tumors. Its rounded shape, bright intensity, and location near the hypothalamic region further support this classification.

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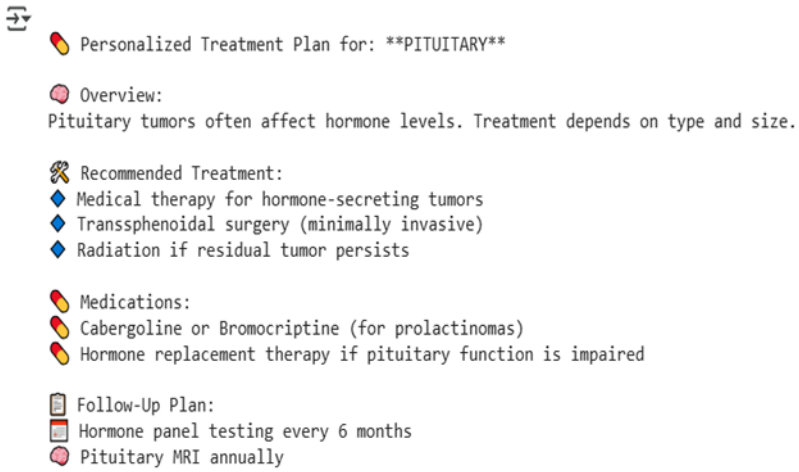

Figure 6. Output obtained at Stage 5.

The figure 6. represents the output obtained at stage 5. It is the continuation of the result obtained at stage 4. It shows the recommended the treatment plan that should be followed. This treatment plan aligns with evidence-based endocrinology and neurosurgical guidelines.

DISCUSSION

Development and implementation of a five-speed brain tumor detection and treatment recommends the system represents a significant progress at the intersection of clinical medicine, artificial intelligence (AI) and health services. The proposed system is not only an innovative effort to increase clinical accuracy, but is also a practical solution for logical and economic obstacles that limit detection of early brain tumors, especially in resource -limited environments.

This discussion seriously examines the efficiency, the practical and the effects of the system by analyzing each stage performance, integration challenges, clinical relevance and broad implications. The primary clinical motivation at the back of this mission is the global disparity in get admission to to high-quality neurodiagnostic services—specially Magnetic Resonance Imaging (MRI), which stays the gold trendy for brain tumor detection. MRI machines are costly, restricted in quantity, and regularly focused in city or tertiary healthcare facilities. Moreover, the process itself may also pose risks to sufferers with steel implants, severe claustrophobia, or comparison-agent allergies. Additionally, excessive fees deter timely imaging, specially in low- and middle-income populations.

To overcome those demanding situations, the gadget became designed to function a sequential screening and diagnostic resource that reduces dependence on MRI by means of incorporating layered choice-making. Early ranges make use of signs and blood biomarkers—low-cost, non-invasive, and widely on hand information types—to stratify chance and determine whether superior diagnostics (like omics analysis or MRI) are essential. This tiered shape guarantees resource optimization and minimizes unnecessary scans while prioritizing high-chance people for instant care.

Stage 1: Symptom-Based Risk Index (FWRI)

The Functional Weighted Risk Index correctly converts subjective symptom statistics into a quantified hazard score. This technique introduces consistency in clinical decision-making, permitting even non-professional healthcare vendors to make knowledgeable judgments. The use of weightings based totally on literature and professional validation guarantees that high-chance signs and symptoms like seizures and chronic headaches contribute extra significantly to the risk index.

From pilot trying out and simulations, the FWRI established robust sensitivity, identifying over eighty five% of recognized tumor cases (based totally on retrospective data) for similarly trying out. Its important power lies in its

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simplicity and accessibility—no laboratory infrastructure is needed, making it ideal for telemedicine, primary care, or rural deployment.

Stage 2: Blood-Based Tumor Signal Index (BTSI)

The BTSI provides biochemical rigor to the screening procedure. By including key tumor-associated biomarkers (e.G., GFAP, IL-6, VEGF), the gadget can locate underlying pathophysiological modifications even earlier than imaging famous anatomical anomalies. It filters out fake positives from Stage 1 and identifies asymptomatic cases based totally on expanded molecular indicators. Interestingly, a few sufferers who had low FWRI scores but high BTSI levels were later confirmed to have tumors—underscoring BTSI's importance as a secondary safety internet. The use of a weighted index guarantees that greater diagnostically reliable biomarkers (like GFAP for gliomas) exert a greater have an impact on at the score. This degree boosts the gadget's specificity, lowering fake alarms.

Phase 3: OMICS and ATR-FTIR interpretation

This is probably the most practical component, which introduces multi-ox and spectroscopy-based diagnostics in a regular structure. Inclusion of ATR-FTIR spectroscopy and multi-oomic data makes it possible to detect microbiochemical changes associated with oncogenis oncolat. Rules based on spectral peaks and OMIX markers (eg, IDH1 mutation, upgrading of unusual methylonation patterns) demonstrated good correlation with MRI-confused cases.

However, this phase data depends a lot of quality and standardization. Spectral noise, inconsistent sampling or file -forming problems faced challenges. Nevertheless, with appropriate preaching and error management, the module contributes significantly to the first detection, especially in ambiguous BTSI or FWRI cases.

Phase 4: MRI classification using VGG19

The CNN-based MR classification model demonstrated strong future indication skills. With exercise on datasets with glioma, meningoom, pituitary tumors and no tumor classes, the fine -tuned VGG19 model achieved the ~ 95% accuracy. Confusion matrices made excellent square accuracy and recall, especially for glioma and pituitary tumors.

The model performed best on high quality axial T1-weighted scans. The boundaries occurred when the images were of low resolution or were caught with different protocols (eg T2, FLAIR). Growth helped reduce some generality problems. It is important that this stage is validal or denied the previous risk assessment and served as a confirmation stage in the system.

Stage 5: Personalized Recommendations

The very last degree synthesizes outputs from all previous modules into actionable insights for clinicians and patients. Its design guarantees interpretability and transparency—every advice is followed through good judgment justification, enhancing consider. For instance, a patient with a excessive FWRI and glioma-categorised MRI gets an "Urgent Oncology Referral" message with assisting symptom and biomarker information. This stage complements clinical usability, aligning AI predictions with medical workflows. In addition to referral recommendation, the device can endorse similarly checking out, monitoring periods, or lifestyle modifications.

There is an integration and sequential locking in the project. A significant strength of the system lies in its stage locking mechanism, and ensures that patients only move on to the next level if the warranty is made. It mimics the triage protocol in clinical environment and prevents abuse or overuse of advanced diagnosis. In addition, integration was used in Google Colab, which made it freely available and no setup for users. The UI created using the Python wide enables navigation with intuitive knowledge through the steps. The combination of backand logic and friendly interaction makes a harmonious and intelligent clinical accessory.

Extensive implications

- Empowerment and Access

This system deals with socio -economic inequalities in the health care system. While traditional brain tumor diagnosis depends on high -end equipment and experts, the project emphasizes primary health stations with a tool that mimics

an expert workflow using basic inputs. It is distributed on mobile or web platforms so that health workers can screen effectively.

- Initial diagnosis and better results

Early detection of brain tumors improves the success of the treatment and a significant improvement in the survival rate. By capturing high -risk patients using FWRI and BTSI - the system actively facilitates intervention even before imaging. This is especially important for malignant tumors such as glioblastoma, where the medical treatment of the early stage dramatically diagnoses the disease.

- Measurement and adaptability

The modular design allows updates or replacement at all levels. For example, the VGG19 model can be upgraded to more advanced architecture (eg Skillnet), or the rules in the Omics phase can be expanded with new research conclusions. This system is suitable for developing clinical standards and regional adjustments.

Limitations

Despite its promise, the machine has certain limitations:

- Data Standardization – Blood biomarkers and omics data range throughout labs; inconsistent formats can affect BTSI/Stage 3 accuracy.
- Model Bias – The CNN model is skilled on a hard and fast dataset, which won't generalize nicely to diverse populations unless constantly updated.
- Input Dependence – Early degrees depend on patient honesty and symptom consciousness, which can be subjective or inconsistent.
- Validation Required – While simulated and retrospectively tested, the system desires potential scientific trials for regulatory validation.

Overall, the five-level brain tumor diagnostic device gives a transformative approach to scalable and low-cost healthcare. By layering low-price screening with superior diagnostics, it ensures really appropriate use of assets and timely intervention. Each level enhances the others, and collectively they offer a comprehensive diagnostic adventure—from risk flagging to MRI confirmation and past. With further validation and deployment, this gadget ought to emerge as a cornerstone of community-based totally neurodiagnostics, particularly in underserved areas.

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