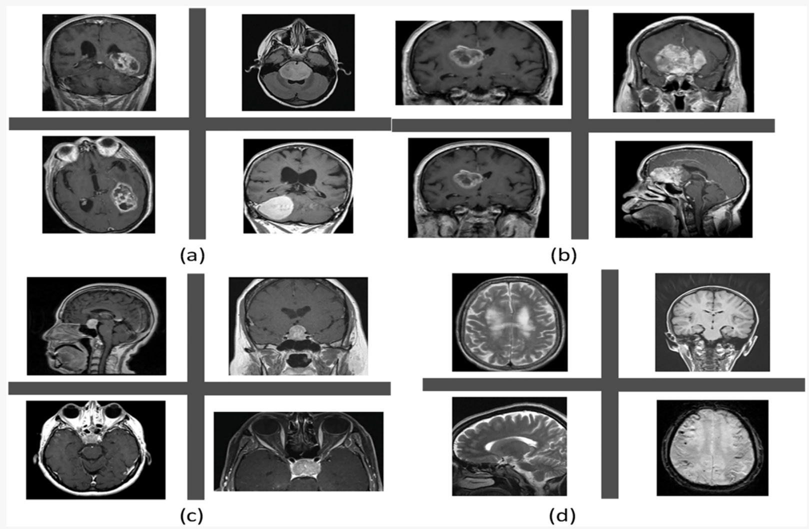
Scientists develop a two-step system for detecting and classifying brain tumors from MRI images

Researchers have developed a new artificial intelligence-based method that could significantly improve the speed and accuracy of brain tumor detection.



MRI scans of (a) Meningioma; (b) Glioma; (c) Pituitary brain tumor; and (d) non tumor samples. Credit: Healthcare Analytics (2026). DOI: https://doi.org/10.1016/j.health.2026.100456

SHARJAH, EMIRATE OF SHARJAH, UNITED ARAB EMIRATES, July 29, 2026 /EINPresswire.com/ -- Researchers have developed a new artificial intelligence-based method that could significantly improve the detection and classification of brain tumors from MRI scans, achieving higher accuracy than conventional diagnostic systems.

The findings, reported in a study published in the journal Healthcare Analytics, suggest that combining advanced AI models can substantially improve diagnostic performance. While traditional approaches based on Convolutional Neural Networks (CNNs) have shown promising results in medical image analysis, the researchers found that integrating CNNs with Long Short-Term Memory (LSTM) networks produced even more accurate outcomes.

The team, led by scientists from the University of Sharjah, designed a two-step system for analyzing brain MRI images. In the first stage, the model analyzes a scan to determine whether a scan contains a tumor. If a tumor is detected, the system proceeds to a second stage, where it classifies the tumor into one of three types: glioma, meningioma, or pituitary tumor.

“The experiments show that model performance improves when progressing from standard CNNs to CNN with LSTM, and then to attention-enhanced architectures,” the researchers write. “Across both stages, attention mechanisms improved feature representation and classification accuracy by capturing more informative global patterns in MRI images.”

Among the models evaluated, the CNN-LSTM architecture enhanced with an attention mechanism proved particularly effective in distinguishing different tumor types. Meanwhile, the Vision Transformer model achieved the highest performance in differentiating tumor scans from non-tumor scans.

According to the authors, “The strong performance of the CNN with LSTM and attention model in the multi-class setting, together with the high accuracy of the Vision Transformer in the binary setting, indicates that these architectures have the potential to support reliable early tumor screening tools in clinical workflows.”

Evaluating deep learning approaches

The study reflects real clinical workflows and enables a fair comparison of different deep learning models used for brain tumor detection. Rather than cataloguing architectures and reporting aggregate performance metrics, the framework is designed to examine how differences in spatial feature extraction, temporal modeling, and global context aggregation influence diagnostic performance under identical clinical conditions.

By evaluating model performance within a standardized preprocessing pipeline and task configuration, the study provides structured insight into how distinct model families capture and represent tumor-relevant information. This approach facilitates meaningful across-model comparison and highlights the complementary strengths of different architectural paradigms without introducing a novel architecture.

The findings are encouraging for efforts to improve the accuracy of brain tumor detection. They come at a time when brain tumors continue to represent a significant cause of cancer-related mortality worldwide, accounting for an estimated quarter of a million deaths annually, according to the World Health Organization (WHO).

The authors based their conclusions on an analysis of 7023 MRI images comprising three tumor categories as well as images of healthy individuals. As they note, “To ensure transparency and reproducibility, all experiments follow a clearly defined image-level evaluation protocol.” They further acknowledge that because full patient identifiers were not consistently available across the source datasets, strict patient-level separation cannot be guaranteed.

To ensure consistency across data sources, a unified preprocessing pipeline was applied to all images. This included resizing scans to a fixed input resolution, intensity normalization, and contrast equalization, thereby minimizing dataset-specific variations and enabling more reliable model evaluation.

Promise of rapid and accurate diagnosis

Detecting brain tumors at the earliest possible stage can significantly improve treatment outcomes, underscoring the significance of the study. Brain tumors remain a serious health problem worldwide, and advances in diagnostic accuracy and speed can improve patients' prognosis and healthcare.

The authors report that their system is computationally efficient, requiring a fraction of a second per scan to detect and classify brain tumors. As they note, "The system showed efficient inference times, averaging 21.6 ms for binary and 17.6 ms for multi-class tasks, supporting its suitability for near real-time clinical applications. Nonetheless, evaluating the model's robustness under low-resolution or highly variable MRI conditions remains an important avenue for future work."

Overall, the study presents a balanced and comprehensive comparison of several leading deep learning approaches for brain tumor diagnosis. Although additional validation will be required before clinical implementation, the findings demonstrate the considerable potential of modern AI techniques to enhance the accuracy, speed, and reliability of brain tumor detection from MRI scans.

The researchers emphasize that "our focus was on the classification performance of different deep learning architectures under a unified and clinically relevant protocol." They further suggest that future research could incorporate interpretability tools, such as feature attribution techniques and lesion-level visualization, to provide greater insight into model decision-making, strengthen the links between AI predictions and tumor pathology, and increase clinicians' trust in the technology.

While the results are encouraging, the authors acknowledge several limitations that should be addressed in future studies. "The experiments were conducted using publicly available MRI datasets, which may not fully represent the diversity of real patients, hospitals, and imaging equipment," they explain. To mitigate this concern, the researchers employed techniques to increase the diversity of training images and improve the model's performance on previously unseen cases.

Nevertheless, they stress that further testing on larger and more diverse clinical datasets will be essential before the system can be deployed in routine medical practice.

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