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MRI-BASED BRAIN TUMOUR CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORKS: A SYSTEMATIC REVIEW AND META-ANALYSIS

Ernest E. Onuiri, Adeyemi John, and Kelechi C. Umeaka

Department of Computer Science, School of Computing, Babcock University, Ilishan-Remo, Ogun State, Nigeria.

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ABSTRACT: *This research assessed advancements in brain tumour classification using convolutional neural networks (CNNs) and MRI data. An analysis of 37 studies highlighted the effectiveness of CNN architectures and pre-processing methods in accurately categorising brain tumours. Issues such as class disparities and model interpretability were identified, prompting recommendations for advanced deep learning techniques, ensemble methods, and diverse datasets to enhance diagnostic accuracy. The findings underscored the importance of these methods in achieving high accuracy, with a maximum rate of 98.80% from 154 MRI images. This systematic study also included a meta-analysis from 2018 to 2022, revealing patterns in MRI cases across demographics and providing insights into healthcare trends.*

KEYWORDS: Convolutional neural networks, deep learning, MRI data, brain tumour classification, accuracy, systematic review, healthcare trends.

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INTRODUCTION

A brain tumour is an abnormal growth of brain tissue, which can be benign or malignant. Benign tumours grow slowly but may still cause complications due to pressure on surrounding areas, while malignant tumours are aggressive. About 70% of brain tumours are benign, and 30% are malignant [1].

Early detection is essential for effective treatment and patient recovery [2]. However, manual MRI anomaly detection for tumour identification and segmentation is time-consuming, error-prone, and potentially risky. To address this, various studies have explored machine learning and deep learning techniques to enhance computer-aided tumour diagnosis and segmentation.

Deep learning has become increasingly popular for creating models that can efficiently and accurately identify and classify tumours, allowing for automation, semi-automation, or hybrid approaches [3]. While brain tumours are typically treated surgically, radiologists still rely on manual identification, diagnosis, and classification using MRI scans, a time-consuming process. MRI provides more detailed insights into brain tumour detection and treatment when compared with other imaging techniques [4].

For years, researchers in image processing and computer vision have explored segmentation and classification using various supervised and unsupervised methods. CNNs have become widely used in industrial automation, medical imaging, and video surveillance [5]. Recently, CNNs have shown remarkable success in medical image segmentation and diagnosis. Conventional methods couldn't train CNNs to learn complex image features, making network design critical [6]. This systematic review aims to consolidate advancements in CNNs for MRI-based brain tumour classification, with a focus on deep learning techniques in medical imaging.

Rationale

This systematic review and meta-analysis are essential for improving early and accurate brain tumour detection, which leads to better treatment options and outcomes for patients. The rapid growth of cancerous tumours and the effects of non-cancerous growths on nearby brain tissues underscores the need for efficient diagnostic techniques. Traditional methods like biopsy, X-ray, and CSF analysis come with risks, including patient discomfort, potential for severe bleeding, and diagnostic inaccuracies.

MRIs revolutionised imaging by providing high-resolution images without radiation exposure. However, the variability in brain tumour size, location, and appearance made precise segmentation and classification difficult. CNNs' segmentation-free feature extraction, eliminating manual feature creation, offered a promising solution [7] – [9].

Aims and Objectives

This research explored advancements in convolutional neural networks (CNNs) for classifying brain tumours using MRI scans, with the following objectives:

i. Evaluate performance metrics and techniques from the literature on CNN-based MRI brain tumour classification.

ii. Compare CNN architectures, pre-processing methods, and dataset characteristics to identify trends and best practices.

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iii. Critically discuss the limitations of CNNs in MRI-based tumour classification and suggest ways to enhance diagnostic accuracy and practical application.

iv. Conduct a meta-analysis to assess findings from various studies on CNNs in brain tumour classification.

MATERIALS AND METHODS

Adhering to the PRISMA guidelines [10], a thorough search for literature covering 2013 through 2024 was conducted using the Scopus and Google Scholar databases.

Inclusion Criteria:

a. Studies focused on brain tumour detection using MRI.

b. Research utilising deep learning techniques, particularly convolutional neural networks (CNNs).

c. Studies showcasing significant advancements in brain tumour identification via MRI.

d. English-languagepublications.

e. Articles published between 2013 and 2024.

Exclusion Criteria:

a. Studies not using MRIs for brain tumour diagnosis.

b. Research not employing deep learning or CNN methods.

c. Studies on MRI-based brain tumour detection without significant advancements.

d. Non-English publications.

e. Articles published outside the 2013–2024 range.

f. Unreadable articles.

g. Non-research literature, including case reports, reviews, editorials, letters, conference abstracts, and meta-analyses.

Information Sources:

An elaborate search strategy had been developed to find important information from various electronic databases, such as Scopus and Google Scholar. To ensure thoroughness in the search process, manual searches of reference lists had also been conducted.

Search Strategy:

A detailed search plan was designed to identify relevant literature and assess progress in using MRI for brain tumour diagnosis. It included terms related to brain tumours, MRI scans, and

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advanced techniques like deep learning and convolutional neural networks (CNNs). The search query was tailored for electronic databases like Scopus.

Search query: 88 document results were retrieved by the following search query on the Scopus database.

TITLE-ABS-KEY ((mri) AND ((brain AND (tumor* OR tumour*)) OR (brain AND (cancer OR carcinoma))) AND detection AND ("Convolutional Neural Networks" OR cnn OR "Deep Learning" OR "Artificial Intelligent" OR ai) AND (classif* OR categor*) AND ("advancement*" OR "improvement*" OR "progress" OR "development*")) AND PUBYEAR > 2013 AND PUBYEAR < 2025 AND PUBYEAR > 2013 AND PUBYEAR < 2025 AND (LIMIT-TO (SRCTYPE , "j")) AND (LIMIT-TO (PUBSTAGE , "final")) AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (LANGUAGE , "English"))TITLE-ABS-KEY ((mri) AND ((brain AND (tumor* OR tumour*)) OR (brain AND (cancer OR carcinoma))) AND detection AND ("Convolutional Neural Networks" OR cnn OR "Deep Learning" OR "Artificial Intelligent" OR ai) AND (classif* OR categor*) AND ("advancement*" OR "improvement*" OR "progress" OR "development*")) AND PUBYEAR > 2013 AND PUBYEAR < 2025 AND PUBYEAR > 2013 AND PUBYEAR < 2025 AND (LIMIT-TO (SRCTYPE , "j")) AND (LIMIT-TO (PUBSTAGE , "final")) AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (LANGUAGE , "English"))

Data management:

Search results from Scopus and Google Scholar were exported in RIS format and screened using Rayyan.ai [11]. A total of 230 documents were identified from Scopus, with filters applied for the publication range (2013-2024), language (English), and open access. After screening for relevance, 44 documents remained.

Google Scholar produced 97 documents, with 36 deemed relevant after the abstract screening.

In total, 80 unique documents were found, and Rayyan identified 4 duplicates, leaving 76. After a full-text review, 46 were excluded, leaving 37 documents for analysis.

See Figure 1 for the PRISMA flow diagram summarising the selection process [12].

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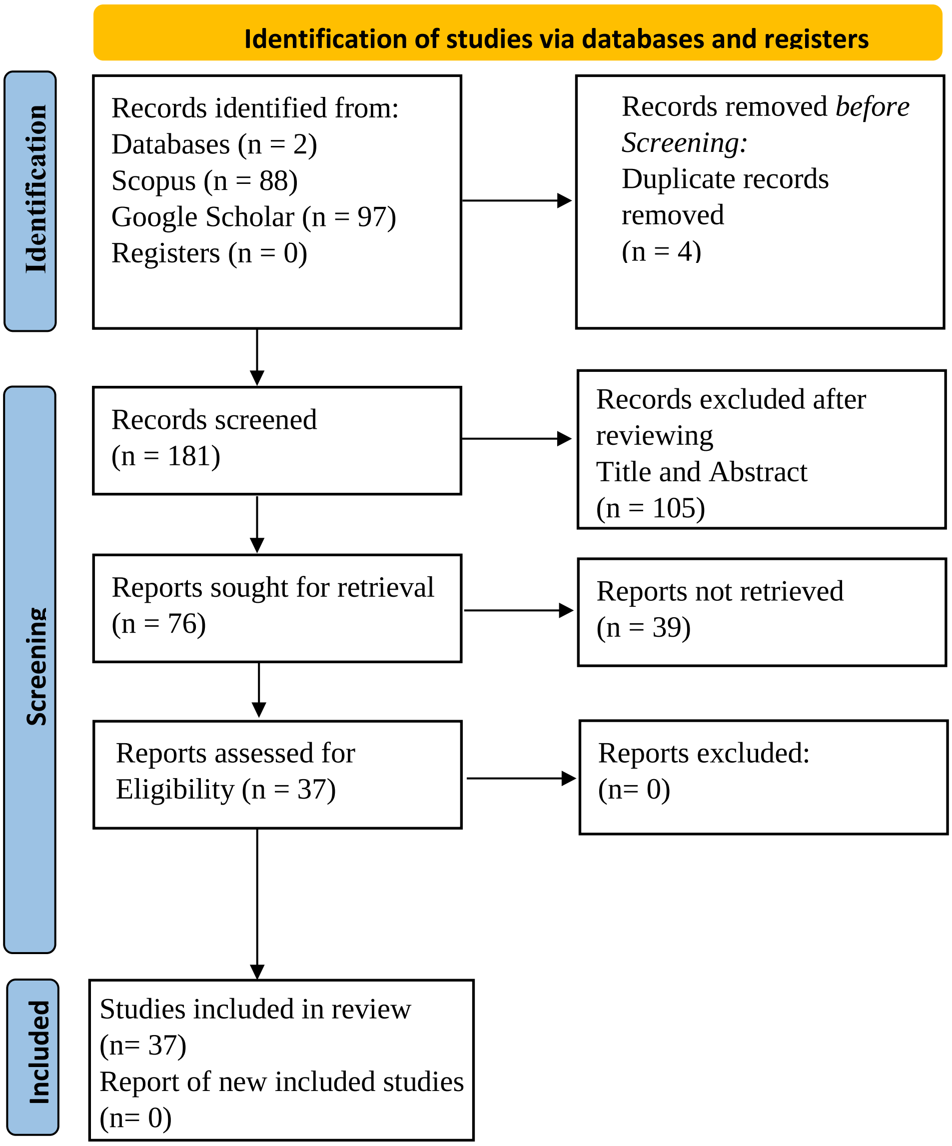

Figure 1: The flowchart displayed the studies that had been screened.

Source: [12]

Data Extraction:

The reviewer employed a systematic data extraction strategy to gather details on study features, methodology, challenges, and improvements in MRI-based brain tumour classification using CNNs. Disagreements during the review were resolved by consulting the relevant literature. The PRISMA flow diagram documented the screening process to ensure transparency and reproducibility.

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Risk of bias:

During the research phase, the screening process was used to thoroughly examine bias. Precise criteria for inclusion were applied to exclude papers that did not meet the search parameters or did not sufficiently focus on the main objective of the review, which was to classify brain cancers using magnetic resonance imaging and convolutional neural networks. The review aimed to uncover and correct any biases present in the chosen studies to ensure the accuracy and dependability of the research results.

RESULT

This study explored advancements in using convolutional neural networks (CNNs) for classifying brain tumours from MRI images, with an emphasis on data pre-processing techniques, CNN model architectures, and key dataset characteristics. The findings demonstrated that CNNs are highly effective in accurately classifying brain tumours, though challenges such as uneven distribution of cancer types and limited model interpretability persist. A meta-analysis of MRI cases from 2018 to 2022 highlighted emerging trends in MRI incidents, contributing to better healthcare resource allocation and planning. Recommendations for improving diagnostic accuracy include using more diverse and balanced datasets, fostering interdisciplinary collaborations, and incorporating more advanced deep learning algorithms. Overall, the study provides valuable insights into current CNN applications and suggests approaches for enhancing diagnostic accuracy and future research.

Table 1. An overview of the research that is included

S/N	Author(s) (Year)	Title	Summary
1	Khan M. et al. (2022) [1]	Accurate brain tumour detection using a deep convolutional neural network	The study used deep learning on MRI scans to classify brain tumours, achieving up to 100% accuracy with a 23-layer CNN and transfer learning, while providing open-source datasets and codes for academic use [1].
2	Anaraki A. K. et al. (2018) [2]	Magnetic resonance imaging-based brain tumour grade classification and grading via convolutional neural networks and genetic algorithms	The study used a CNN to classify 3,064 MRI images, achieving high accuracy in detecting pituitary tumours, meningiomas, and gliomas [2].

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3	Nazir M. et al. 2021 [3]	The role of deep learning in brain tumour detection and classification	The article reviewed recent studies on brain tumour detection using MRI, emphasising deep learning techniques and critically assessing methods from 2015 to 2020 [3]
4	Abd-Ellah M. K. et al. (2019) [4]	TPUAR-net: two parallel U-nets with an asymmetric residual-based deep convolutional neural network for brain tumour segmentation	The study utilised TPUAR-Nets, an asymmetric residual deep CNN, for brain tumour segmentation in MRI images, achieving a maximum Dice score of 0.89 on the BRATS 2017 dataset [4].
5	Kaldera H. N. T. K. et al. (2019) [5]	Brain Tumour Classification and Segmentation Using Faster R-CNN	The study automated brain tumour classification and segmentation in MRI using Faster R-CNN and CNN, achieving 100% accuracy for meningiomas and 87.5% for gliomas, validated by manual analysis [5].
6	Lamrani D. et al. (2022) [6]	Brain tumour detection using MRI images and a convolutional neural network.	The paper explored CNNs for brain cancer detection in MRI images, achieving 88%-91% accuracy with VGG19 and Inception V3, and 96% with a recommended model [6].
7	Bhandari A. et al. (2020) [7]	Convolutional neural networks for brain tumour segmentation	The article reviewed CNNs for brain tumour segmentation, focusing on radionics to predict clinical outcomes and improve segmentation accuracy and patient care [7].
8	Bernal J. et al. (2019) [8]	Deep convolutional neural networks for brain image analysis on magnetic resonance imaging: a review	The paper reviewed CNN approaches in brain MRI analysis, discussing architecture, techniques, advantages, disadvantages, public datasets, and future research directions [8].

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9	Min Z et al. (2020) [9]	Deep-Learning Detection of Cancer Metastases to the Brain on MRI	The study used 3D T1-weighted MRI and Faster R-CNN to detect brain metastases, achieving 96% sensitivity and a ROC curve area of 0.79 from 361 images [9].
10	Khan S. et al. (2021) [13]	A review of traditional machine learning and deep learning models for WBC classification in blood smear images	The article explored advancements in medical image analysis for brain tumours and leukaemia detection, highlighting CNNs for improved diagnostic accuracy and suggesting future research directions [13].
11	Bacchi S. et al. (2019) [14]	Deep learning in the detection of high-grade glioma recurrence using multiple MRI sequences: A pilot study	The article focused on using deep learning to distinguish treatment-related changes from high-grade glioma progression in MRI scans. CNN models achieved 0.82 accuracy and 0.86 F1 score, highlighting deep learning's effectiveness [14].
12	Ahammed M. et al. (2019) [15]	Glioma Tumour Grade Identification Using Artificial Intelligent Techniques	The research presented a system for diagnosing glioma grades from MRI scans using VGG-19 and Wndchrm classifiers. VGG-19 achieved 92.86% accuracy, outperforming Wndchrm through data augmentation and feature selection [15].
13	Hasan et al. (2020) [16]	MRI brain classification using the quantum entropy LBP and deep-learning-based features	The study improved brain cancer detection using MRI by integrating quantum calculus with deep learning and an LSTM network, achieving 98.80% accuracy in classifying 154 MRI brain images [16].
14	Alshayeji M. et al. (2021) [17]	Enhanced brain tumour classification using an optimised multi-layered	The research presented a deep-learning method for brain tumour classification, utilising layer-by-layer neural networks and Bayesian optimisation. It achieved 97.37% accuracy, surpassing previous classification efforts [17].

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		convolutional neural network architecture	
15	Thaha M. M. et al. (2019) [18]	Brain Tumour Segmentation Using Convolutional Neural Networks in MRI Images	The study presented an Enhanced Convolutional Neural Network (ECNN) optimised with the BAT method for automatic brain tumour segmentation in MRI images, improving accuracy and outperforming existing methods in precision and recall [18].
16	Grøvik E et al. (2020) [19]	Deep learning enables automatic detection and segmentation of brain metastases on multisequence MRI.	The project used a fully convolutional neural network (CNN) to segment brain metastases in MRI data from 156 patients. It achieved an AUC of 0.98, accuracy of 0.79, recall of 0.53, and a Dice score of 0.79, showing potential to enhance clinical radiography for brain metastases [19]
17	Kumar R.L. et al. (2021) [20]	Multi-class brain tumour classification using residual networks and global average pooling	The study emphasised the need for automated brain tumour identification amid rising incidences. It proposed integrating global average pooling and ResNet-50 into a deep network model, evaluated with 3,064 MRI scans from three tumour types, addressing challenges like overfitting [20].
19	Kermi A. et al. (2019) [22]	Deep convolutional neural networks using U-Net for automatic brain tumour segmentation in multimodal MRI volumes	The paper presented an automated brain tumour segmentation method using 2D Deep Convolutional Neural Networks (DNNs) on 3D MRI scans, achieving dice scores of 0.783 for enhancing tumour, 0.868 for whole tumour, and 0.805 for tumour core, similar to neuro-radiologists' manual segmentation [22].
20	Karayegen G. et al. (2021) [23]	Brain tumour prediction on MR images with semantic segmentation by using a deep learning network and 3D imaging of	The study found that Convolutional Neural Networks (CNNs) achieve 91.72% accuracy in tumour prediction and 99.76% in background classification of MRI scans. Future research should focus on larger patch sizes and 3D brain models. A similarity ratio of 86.95% was achieved with predicted labels, surpassing other methods in F-score performance [23].

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		the tumour region	
21	Abiwinanda N. et al. (2019) [24]	Brain tumour classification using a convolutional neural network	The study trained a Convolutional Neural Network (CNN) on 3,064 T1-weighted CE-MRI brain tumour images, achieving 98.51% training accuracy and 84.19% validation accuracy with 500 training images and 200 validation images per class [24].
22	Gurunathan A. et al. (2021) [25]	Detection and diagnosis of brain tumours using deep learning convolutional neural networks	MRI data assessed a deep learning system for brain tumour identification and segmentation using convolutional neural networks (CNNs). Built with Python, the system achieved an average accuracy of 98.3% (98.6% for normal images and 98% for abnormal ones) [25].
23	Bhanothu Y. et al. (2020) [26]	Detection and classification of brain tumours in MRI images using a deep convolutional network	This research presented a faster R-CNN system with a region proposal network (RPN) for locating brain tumours in MRI images, achieving average precision of 75.18% for gliomas, 89.45% for meningiomas, and 68.18% for pituitary tumours, with an overall mean average precision of 77.60% [26].
24	Pathak K. et al. (2019) [27]	Classification of brain tumours using a convolutional neural network	This study proposed a method for brain tumour classification and segmentation using a CNN and watershed algorithm, achieving 98% accuracy by using smaller kernels to prevent overfitting and identify tumour regions [27].
25	Madhupriya G. et al. (2019) [28]	Brain tumour segmentation with deep learning techniques	The study proposed a deep learning approach combining CNNs and PNNs to segment brain tumours in MRI images. Using 3x3 and 7x7 filters, the model accurately identified abnormal tissues and achieved precise tumour segmentation [28].
26	Pei L. et al. (2020) [29]	Brain tumour classification using a 3D convolutional neural network	The paper proposed a two-phase deep learning method for brain tumour classification, starting with segmentation via multimodal MRI and following classification. A 3D neural network achieved a validation score of 0.749 and an F1 score of 0.764 on the CPM: Rad-Path dataset [29].
27	Ngo D-K et al. (2020) [30]	Multi-task learning for small brain	The paper tackled the challenge of accurately segmenting small brain tumours for early detection, proposing a method using dilated convolution and multi-task learning to improve

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		tumour segmentation from MRI	performance without increasing computational costs. Experimental results confirmed its effectiveness in identifying small tumours [30].
28	Badža M et al. (2020) [31]	Classification of brain tumours from MRI images using a convolutional neural network	The paper introduced a novel CNN for classifying three brain cancer types using T1-weighted contrast-enhanced MRI, achieving 96.56% accuracy during cross-validation. This simpler architecture demonstrates strong generalisation, suggesting its potential as an effective decision-support tool for radiologists [31].
29	Wang W. et al. (2020) [32]	Learning Methods of Convolutional Neural Networks Combined with Image Feature Extraction in Brain Tumour Detection	The study improved brain tumour detection by extracting key features and reducing correlations using linear transformations. Using the GBM dataset, it identified glioblastoma and integrated MRI with CNNs for better tumour identification, offering insights for future research [32].
30	Wang G. et al. (2019) [33]	Automatic brain tumour segmentation using convolutional neural networks with test-time augmentation	The study explored the impact of test-time augmentation on CNN performance for brain tumour segmentation using the BraTS 2018 dataset. Techniques such as 3D rotation, flipping, and random noise improved segmentation accuracy and reliability of uncertainty estimates, enhancing CNN capabilities [33].
31	Kumar S. et al. (2019) [34]	Semantic segmentation using deep learning for brain tumour MRI via fully convolutional neural networks	The paper introduced a method for brain tumour segmentation using convolutional neural networks (CNNs), highlighting a fully convolutional network (FCN) that improved accuracy and reduced computational costs. The FCN showed significant accuracy gains on the NYUD dataset, demonstrating its potential in medical imaging [34].
32	Díaz-Pernas F et al. (2021) [35]	A deep learning approach for brain tumour classification and segmentation	The paper introduced a fully automatic model for brain tumour segmentation and classification using a multiscale deep convolutional network. Analysing MRI scans without pre-processing, it achieved a classification accuracy of 0.973 on 3,064 slices from 233 patients [35].

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		using a multiscale convolutional neural network	
33	Deng Wu et al. (2019) [36]	Brain Tumour Segmentation Based on an Improved Convolutional Neural Network in Combination with Non-quantifiable Local Texture Features	The study proposed a brain tumour segmentation method combining fully convolutional neural networks (FCNN) with dense micro-block difference features (DMDF). Using Fisher vector encoding and deconvolution layers, it achieved an average Dice index of 90.98%, improving accuracy and real-time performance [36].
34	Woźniak M et al. (2023) [37]	Deep neural network correlation learning mechanism for CT brain tumour detection	The paper introduced a correlation learning mechanism (CLM) to enhance CNNs for CT brain scan evaluation, using a support network to improve filter selection. The model achieved 96% accuracy, with precision and recall scores of 95% [37].
35	A. Z. Shirazi *et al.* (2020) [38]	The application of deep convolutional neural networks to brain cancer images: a survey	The study highlighted the potential of deep learning, particularly CNNs, to revolutionise brain cancer image analysis, leading to more personalised therapies and accurate diagnoses. However, further advancements are needed to fully realise its benefits for personalised brain cancer treatment [38].
36	Gokila Brindha, P. et al. (2021) [39]	Brain tumour detection from MRI images using deep learning techniques	The research used MRI images and deep learning algorithms for brain tumour diagnosis, proposing a CNN and custom ANN for accurate and fast predictions to assist radiologists and support timely treatment [39].
37	Reyes, D et al/(2024) [40]	Performance of convolutional neural networks for the classification of brain tumours using	The research evaluated CNN architectures, achieving 98.7% accuracy in brain tumour classification with MRI datasets. Mobile Net and EfficientNetB0 excelled in efficiency, highlighting the effectiveness of CNNs through transfer learning [40].

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		magnetic resonance imaging	

FINDINGS

This systematic evaluation of 37 papers on MRI-based brain tumour classification using convolutional neural networks (CNNs) yielded important insights into the field's developments and challenges.

The findings indicate that CNNs have become essential for classifying brain tumours from MRI data, demonstrating ongoing advancements to enhance accuracy and efficiency. The use of advanced deep learning techniques has positively impacted CNN-based classification performance.

Pre-processing techniques played a crucial role in optimising input data, significantly contributing to high classification accuracy through careful augmentation of MRI images. Reliable data processing pipelines emphasise the importance of feature extraction and data quality.

However, challenges such as class imbalances and model interpretability remain. These issues highlight the need for further research to enhance transparency and data distribution in CNN-based systems.

Future research should explore advanced deep learning techniques and diverse datasets to improve the accuracy and clinical applicability of automated brain tumour classification tools.

In summary, this review underscored the progress in MRI-based brain tumour classification with CNNs while identifying areas for improvement, emphasising the need for collaborative research to enhance early and accurate diagnosis.

Report on Meta-Analysis

This study conducted a meta-analysis of MRI scan cases from groups A to H (2018–2022) using Graph Pad Prism, providing insights into healthcare trends and resource allocation. The research focused on convolutional neural networks (CNNs) to improve brain cancer detection. CNN models demonstrated high accuracy in classifying brain tumours and identifying gliomas, meningiomas, and pituitary tumours. The meta-analysis highlighted advancements in brain tumour imaging, enhancing classification accuracy and efficiency through CNN applications.

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METHODS

Data on MRI scan cases for groups A through H were collected and entered into Graph Pad Prism, a statistical analysis tool. The data was thoroughly reviewed for quality and completeness before being analysed. Descriptive statistics were then calculated for each group's MRI scan cases across the five years statistics included measures of central tendency and variability, such as the mean, minimum, and maximum values.

Table 2. Data Extracted Table

Data Extracted: From Systematically Reviewed Publications

	Group A MRI-Scan	Group B MRI-Scan	Group C MRI-Scan	Group D MRI-Scan	Group E MRI-Scan	Group F MRI-Scan	Group G MRI-Scan	Group H MRI-Scan
CASE	3064	62000	3000	361	154	156	257	252
2018	5							
2019	8	1						
2020				4	10	7		
2021	6						3	9
2022			2					

Table 3. Descriptive Statistic Table

Descriptive Statistics Table

	3064	62000	3000	361	154	156	257	252
Number of values	3	1	1	1	1	1	1	1
Minimum	5.000	1.000	2.000	4.000	10.00	7.000	3.000	9.000
Maximum	8.000	1.000	2.000	4.000	10.00	7.000	3.000	9.000
Range	3.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Mean	6.333	1.000	2.000	4.000	10.00	7.000	3.000	9.000
Std. Deviation	1.528	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Std. Error of Mean	0.8819	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Lower 95% CI of mean	2.539							
Upper 95% CI of mean	10.13							
Coefficient of variation	24.12 %	0.000 %	0.000 %	0.000 %	0.000 %	0.000 %	0.000 %	0.000 %

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Lower 95% CI of geo. mean	3.450							
Upper 95% CI of geo. mean	11.20							
Skewness	0.9352							
Kurtosis								
Sum	19.00	1.000	2.000	4.000	10.00	7.000	3.000	9.000

VISUALISED DATA

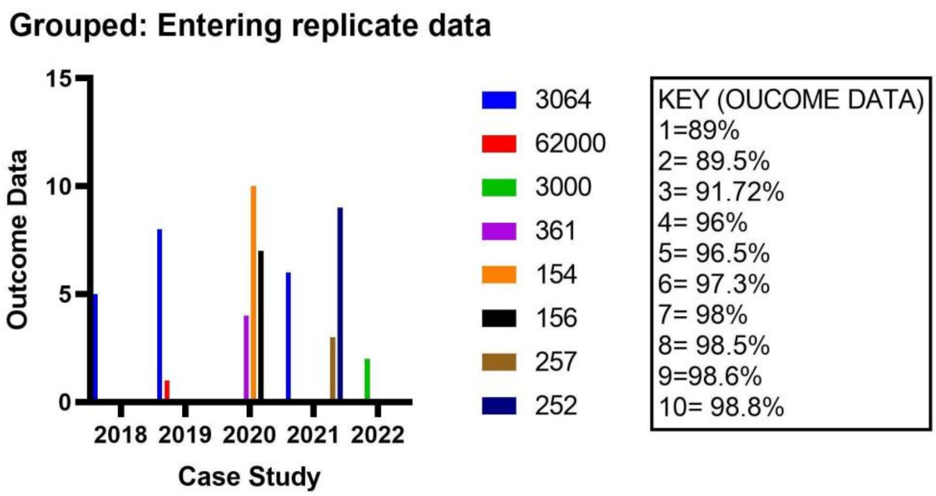

Figure 2: Visualised Data

Source: *By the Researcher*

The analysis revealed diverse MRI scan patterns across groups and years. Group A showed significant fluctuations, particularly a decline from 2018 to 2022. Group B maintained a stable trend, while Groups C, E, and H saw increases in specific years. Group D had minimal data, and Group G recorded the lowest cases in 2020.

This meta-analysis aimed to improve brain tumour examination through deep learning techniques, particularly convolutional neural networks (CNNs). Various studies highlighted the effectiveness of CNN models in accurately classifying different brain tumours, enabling timely diagnoses.

Overall, the findings underscore advancements in brain tumour imaging through CNNs and deep learning, enhancing classification speed and accuracy. Future research could focus on using external GPU devices for larger datasets and increasing patch sizes for better pixel categorisation.

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DISCUSSION

This systematic study evaluates CNN-based brain tumour classification, highlighting the importance of CNN design, pre-processing techniques, and dataset characteristics in achieving optimal results. Key areas for improvement include addressing class imbalances and enhancing model interpretability, which is essential for clinical usability and accurate diagnosis.

The paper recommends exploring advanced deep learning techniques, collaborative approaches, and integrating diverse datasets to improve diagnostic accuracy. Advanced methods can enhance the resilience of CNN models, while collaborative techniques, like ensemble methods, can leverage multiple models for better performance.

Integrating varied datasets is crucial for recognising complex patterns in brain tumours and improving generalisation across different demographics. This comprehensive approach aims to develop robust CNN-based systems that effectively assist medical practitioners in diagnosis and treatment.

In summary, ongoing innovation and collaboration are vital for advancing CNN-based brain tumour classification. By addressing key challenges and utilising diverse datasets, researchers can enhance the clinical utility and accuracy of these tools, ultimately improving patient outcomes. The study underscores the significant progress made through CNNs in medical imaging, with future strategies like using external GPU devices for larger datasets suggested to further enhance brain tumour detection.

CONCLUSION

The review of 37 articles offers significant insights into CNN-based MRI brain tumour classification research. It highlights the importance of CNN designs and pre-processing techniques in achieving high classification accuracy. Future research directions aim to address challenges and enhance diagnostic performance through diverse datasets and advanced deep learning algorithms.

This work underscores the transformative potential of deep learning in medical imaging, demonstrating reliable classification of brain tumours in MRI images. The comprehensive analysis showcases advancements in CNN architectures and pre-processing techniques, enhancing clinical relevance and diagnostic accuracy.

The meta-analysis of MRI cases over five years reveals progress in brain tumour imaging due to CNNs and deep learning. Future studies could explore using external GPU devices for larger datasets and enhance pixel classification with larger patch sizes, improving understanding and identifying areas for further development in CNN-based brain tumour classification.

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AUTHORS' CONTRIBUTIONS

Dr. Ernest Onuiri conceived the idea for this systematic review. Kelechi Umeaka assumed primary authorship and played a crucial role in the development and execution of the review. Both Dr. Ernest Onuiri and Kelechi Umeaka provided feedback that was incorporated into the protocol plan developed by Kelechi Umeaka. All contributing authors reviewed and approved the final manuscript.

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