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# A Systematic Analysis of Neural Networks, Fuzzy Logic and Genetic Algorithms in Tumor Classification

**Ahmed Al-Ashoor [1,2,*], Ferenc Lilik [3] and Szilvia Nagy [3,*]**

[1] Doctoral School of Multidisciplinary Engineering Sciences, Széchenyi István University, 9026 Győr, Hungary
[2] College of Pharmacy, University of Basrah, Basrah 61004, Iraq
[3] Department of Telecommunications, Széchenyi István University, 9026 Győr, Hungary; lilikf@sze.hu
* Correspondence: ahmed89.alashoor89@gmail.com (A.A.-A.); nagysz@sze.hu (S.N.)

**Abstract:** This study explores existing research on neural networks, fuzzy logic-based models, and genetic algorithms applied to brain tumor classification. A systematic review of 53 studies was conducted following PRISMA guidelines, covering search strategy, selection criteria, quality assessment, and data extraction. Articles were collected from three scientific databases: Web of Science, Scopus, and IEEE. The review primarily focuses on practical contributions, with most studies emphasizing applications over conceptual insights. Key methods in the field demonstrate significant impact and innovation. Commonly used training and testing mechanisms include dataset splitting, augmentation, and validation techniques, highlighting their widespread adoption for performance evaluation. The analysis of evaluation metrics shows that accuracy and the DICE score are the most frequently used, alongside sensitivity, specificity, recall, and other domain-specific measures. The variety of metrics underscores the need for tailored approaches based on dataset characteristics and research objectives. By highlighting trends, challenges, and research gaps, this review provides actionable insights for advancing BTC research. It offers a comprehensive overview of techniques and evaluation methods to guide future developments in this critical domain.

**Keywords:** brain tumor classification; magnetic resonance imaging (MRI); deep learning and machine learning models; segmentation and evaluation metrics

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## 1. Introduction

Brain tumors are among the most dangerous types of cancer and require precise and timely classification to improve patient outcomes. Traditional methods of brain tumor diagnosis rely heavily on manual interpretation by radiologists, which can be time-consuming, subjective, and prone to errors. Early diagnosis is crucial in determining the appropriate treatment path, including surgery, radiotherapy, or chemotherapy [1]. In recent years, integrating AI-based technologies—such as artificial neural networks (ANNs), fuzzy logic-based neural networks, and genetic algorithms—into brain tumor diagnosis has transformed the field. These AI-based technologies enable automatic, high-speed, and accurate tumor classification, enhance clinical decision-making, and reduce human error.

Artificial neural networks (ANNs) have received significant attention in medical image analysis and classification due to their ability to solve complex computational problems, particularly in medical diagnostics that require high accuracy [2]. One of the key applications of ANNs is brain tumor classification (BTC). BTC systems rely on medical imaging data, such as MRI scans, to detect, diagnose, and plan treatment for brain tumors at an early stage [3]. Additionally, BTC systems assist radiologists and clinicians in accurately

distinguishing between different types of brain tumors, such as gliomas, meningiomas, and pituitary tumors [1]. The typical workflow of BTC algorithms consists of several key stages: (1) data acquisition, where MRI scans are collected; (2) preprocessing, which includes noise reduction and image normalization to enhance quality; (3) segmentation, which identifies regions of interest, particularly tumor areas; (4) feature extraction, where characteristics such as tumor size and texture are identified; (5) classification, using techniques like ANNs, fuzzy logic-based neural networks (FLNNs), or genetic algorithms (GAs) to determine the tumor type; and (6) evaluation, where the model's performance is assessed based on accuracy, precision, recall, and other relevant metrics [4].

Deep learning models, a subset of ANNs, have demonstrated their ability to learn complex patterns in data. Numerous studies have explored the effectiveness of popular deep learning models, such as convolutional neural networks (CNNs), in BTC [5]. CNNs are particularly well-suited for image processing tasks and have been widely applied in medical imaging. However, despite their success, several challenges remain. One major challenge is the variability in datasets used across different studies, often leading to inconsistent performance when applied to new or diverse patient populations. Another challenge is comparing results across studies due to the lack of standardized evaluation metrics and transparent training and testing mechanisms [6].

Fuzzy logic-based neural networks (FLNNs) represent another promising BTC approach. FLNNs combine the strengths of fuzzy logic and neural networks to address uncertainties and imprecise data in medical image classification [7]. Fuzzy logic enables the system to interpret data more flexibly using linguistic variables such as "small", "medium", or "large" [8]. FLNNs enhance the accuracy of BTC systems by mitigating noise and ambiguity often present in medical images. Combining fuzzy rules derived from expert knowledge and neural network learning capabilities improves the system's interpretability and robustness.

Another approach involves using GAs inspired by natural selection. GAs are employed to optimize the parameters of ANNs and to select the most relevant features from MRI images for accurate classification. Integrating GAs into ANNs enhances BTC accuracy by optimizing feature selection and adjusting the hyperparameters of ANN models. Moreover, the ability of GAs to evolve through crossover and mutation processes enables efficient optimization of complex models such as ANNs [9].

The primary challenge in applying ANNs, FLNNs, and GAs in BTC lies in the diversity and inconsistency of methods, datasets, and evaluation metrics. Additionally, the lack of standardized datasets and preprocessing techniques complicates the assessment of model generalizability. This systematic review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [10]. The study aims to consolidate the current body of knowledge in this field by extracting and analyzing key data from 53 relevant studies. It examines various types of neural networks, fuzzy logic-based models, genetic algorithms, the datasets used, segmentation approaches, and evaluation metrics. This review provides insights to guide future BTC research and development by identifying common trends, research gaps, and challenges.

This study aims to answer the following questions:

- What are the trends in applying ANNs for segmentation tasks, as reflected in the types of ANNs, datasets, and segmentation approaches used in the recent literature?
- How do different training and testing mechanisms and evaluation metrics correlate with performance outcomes (e.g., accuracy, precision) in ANN-based segmentation models across the selected papers?

Unlike previous systematic reviews that primarily focus on specific models, this study uniquely integrates and compares artificial neural networks, fuzzy logic-based neural

networks, and genetic algorithms within the same systematic framework. Moreover, it contributes by classifying studies into conceptual and practical categories, detailing the train-test mechanisms, segmentation approaches, and evaluation metrics.

The remainder of this paper is organized as follows: Section 2 explains the study's methodology. Section 3 presents the descriptive analysis of the selected studies. Section 4 provides qualitative insights and discusses key findings. Finally, Section 5 concludes the research with recommendations for future work.

## 2. Methodology

The PRISMA methodology is one of the most widely used frameworks for reporting meta-analyses and systematic reviews [10]. It has been applied in various research fields, including deep learning, machine learning methods, and IPv6 security issues [11]. Figure 1 illustrates the methodology followed in this paper.

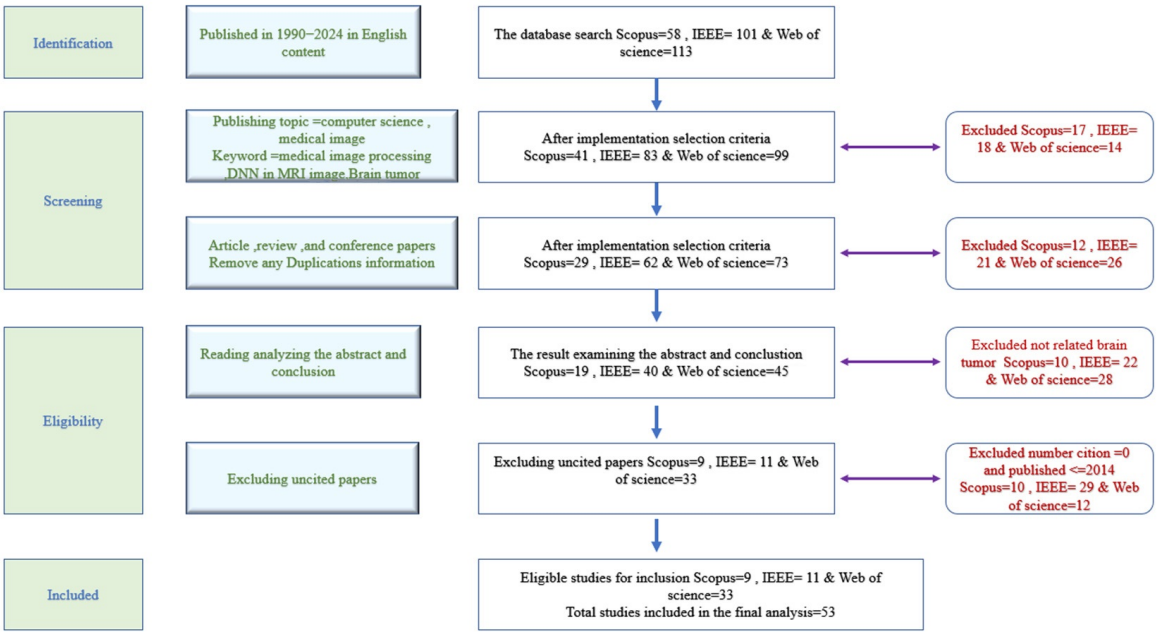



**Figure 1.** Research Methodology.

### *2.1. PRISMA Basic Spets*

The PRISMA framework consists of four main stages:

1. Search strategy;
2. Selection criteria;
3. Ensuring result quality.
4. Data Extraction

Systematic research requires defining and developing a search strategy to identify relevant literature. This strategy includes three major scientific databases: Web of Science, Scopus, and IEEE. These databases are among the largest repositories of scientific and technical publications and contain a wealth of high-quality research. One of the search terms used in the databases was "brain tumor". In the initial research phase, the search scope was limited to studies published between 2014 and 2024.

The study included research from all countries but was limited to publications written in English. In the Web of Science database, the "publication topic" option was used as a filter to focus on image processing with medical images. This refinement reduced the number of studies from 113 to 99, as 14 were excluded. In the IEEE database, the "publishing topic" criterion was applied to focus on medical image analysis, excluding 18 studies from a total

of 101, leaving 83 relevant studies. For the Scopus database, the selection criterion was based on "keywords", yielding 41 relevant papers out of 58, with 17 papers excluded due to irrelevance. The final number of selected research papers across all databases was 223. Table 1 presents the selection criteria applied in this study.

**Table 1.** Selection criteria.

| | **Web of Science** | **IEEE** | **Scopus** |
|---|---|---|---|
| Keyword: | "brain tumor" | "brain tumor" | "brain tumor" |
| Criterion applied: | "publication topic" | "publishing topic" | "keyword" |
| Value of criterion: | Image processing with a medical image | Analysis of medical image | Image processing in the medical field |
| Records returned: | 113 | 101 | 58 |
| Record excluded: | 14 | 18 | 17 |
| Records extracted: | 99 | 83 | 41 |

Three main steps were taken to improve the quality of the search.

Firstly, the "document type" field was used in the Web of Science and Scopus databases to filter search results, while the "document identifier" field was applied in the IEEE database. Additionally, a filter was implemented to exclude review articles and conference papers. As a result, six articles were excluded from Web of Science, two from Scopus, and four from IEEE.

The second step was removing the duplicates, which was performed using the duplicate removal features in Microsoft Excel in two stages:

A. Removing duplicates within individual databases

- Web of Science: in total, 5 papers removed;
- IEEE: in total, 4 papers removed;
- Scopus: in total, 10 papers removed.

B. Matching across all three databases and removing duplicates

- Web of Science: in total, 15 additional papers removed;
- IEEE: in total, 13 additional papers removed.

This step excluded 26 papers from Web of Science, 21 from IEEE, and 12 from Scopus.

The last step, evaluation step was divided into two parts. The first part focused on analyzing the abstracts of the papers, while the second part examined citations and the year of publication.

A. Extracting articles that employed magnetic resonance imaging (MRI)
The abstract summarizes the research work, making it useful for identifying relevant studies. Analyzing and evaluating the abstract content helped isolate research that specifically employed MRI. Any study that did not rely on MRI for conducting experiments was excluded. As a result, 28 articles were excluded from Web of Science, 22 from IEEE, and 10 from the Scopus database.

B. Extracting highly cited articles
This step involved identifying and selecting articles with high citation counts from the past decade (2014–2024). As a result, 12 papers were excluded from Web of Science, 29 from IEEE, and 10 from the Scopus database.

The statistical summary of the studies is presented in Table 2, under the Stage of Maintaining Quality section.

**Table 2.** Stage of maintaining quality.

| Task | Stepping | Excluded Papers | | |
|---|---|---|---|---|
| | | Web of Science | IEEE | Scopus |
| Filter | Counting articles, reviews, and conference papers | 6 | 4 | 2 |
| Removal duplicated | Exclusion based on duplicates in the same database | 5 | 4 | 10 |
| | Exclusion based on duplicates between the three databases | 15 | 13 | 0 |
| Evaluation | Analyzing the abstract papers | 28 | 22 | 10 |
| | Citations and the year of publication of papers | 12 | 29 | 10 |

### 2.2. Data Analysis

The data analysis focused on identifying key insights concerning the review's principles and research questions. Classification and analysis were conducted based on titles, keywords, and abstracts, as they contained the primary data and were examined rigorously. This study followed the same approach as Abdullah et al. [11].

Each article was classified as either a "conceptual contribution" or a "practical contribution".

- A conceptual contribution refers to descriptive, comparative, analytical, or review-based research;
- A practical contribution indicates that the research involved designing, developing, implementing a program, or presenting a novel algorithm.

Another level of analysis was based on the research domain. This study explores brain tumor classification, focusing on the parameters used in related research. For instance, some researchers aim to classify and detect brain tumors using MRI images and apply machine learning or deep learning techniques. Thus, based on the applied methods, this classification approach primarily relies on MRI images for brain tumor detection.

The study considers two primary perspectives:

1. The "field" perspective examines the specific parameters researchers worked with;
2. The "parameter" perspective reflects the targeted application areas.

Additionally, a third classification focuses on the specific problems the studies aimed to address, such as data preprocessing or brain tumor classification.

## 3. Results

This section presents the results of applying the PRISMA framework, including a descriptive analysis and classification of the literature.

### 3.1. Descriptive Analysis

In response to the first research question, "What are the trends in applying ANNs for segmentation tasks, as reflected in the types of ANNs, datasets, and segmentation approaches used in the recent literature?" several descriptive statistical analyses were conducted. The following subsections detail these statistical analyses.

### *3.2. Trends in Citations and Publications over Time*

This subsection examines citation trends and the number of publications from 2014 to 2024 across different indexing platforms, including IEEE, Scopus, and Web of Science. Figures 2–4 illustrate these trends, providing insights into the growth and impact of research on ANNs for segmentation tasks over the past decade.

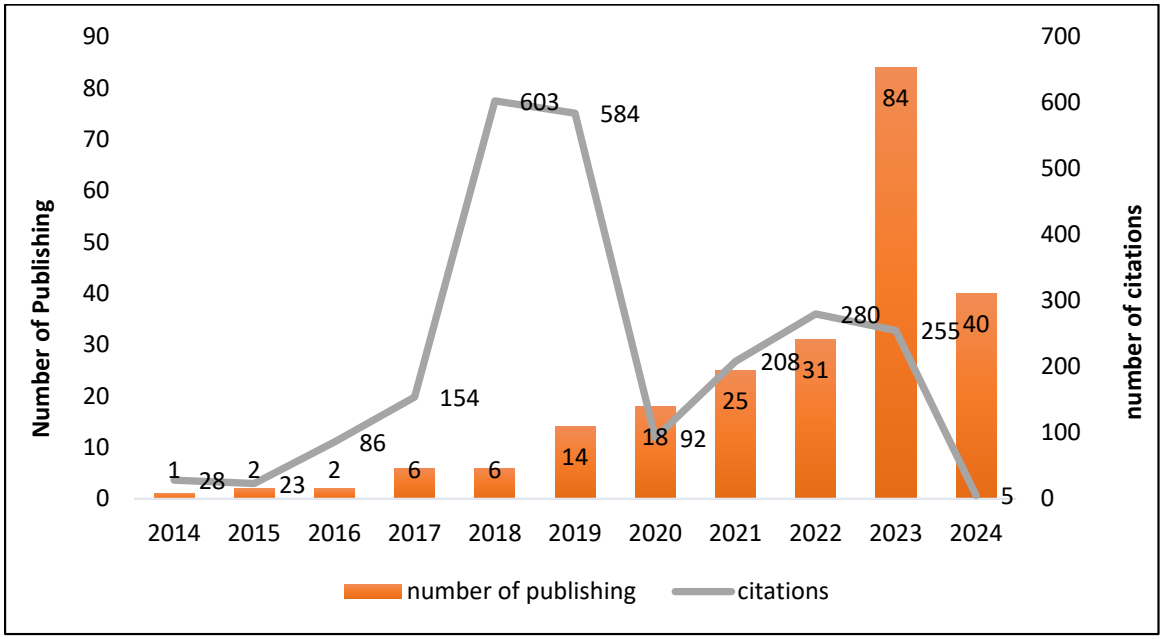



**Figure 2.** Number of citations and publications per year from 2014 to 2024 in IEEE.

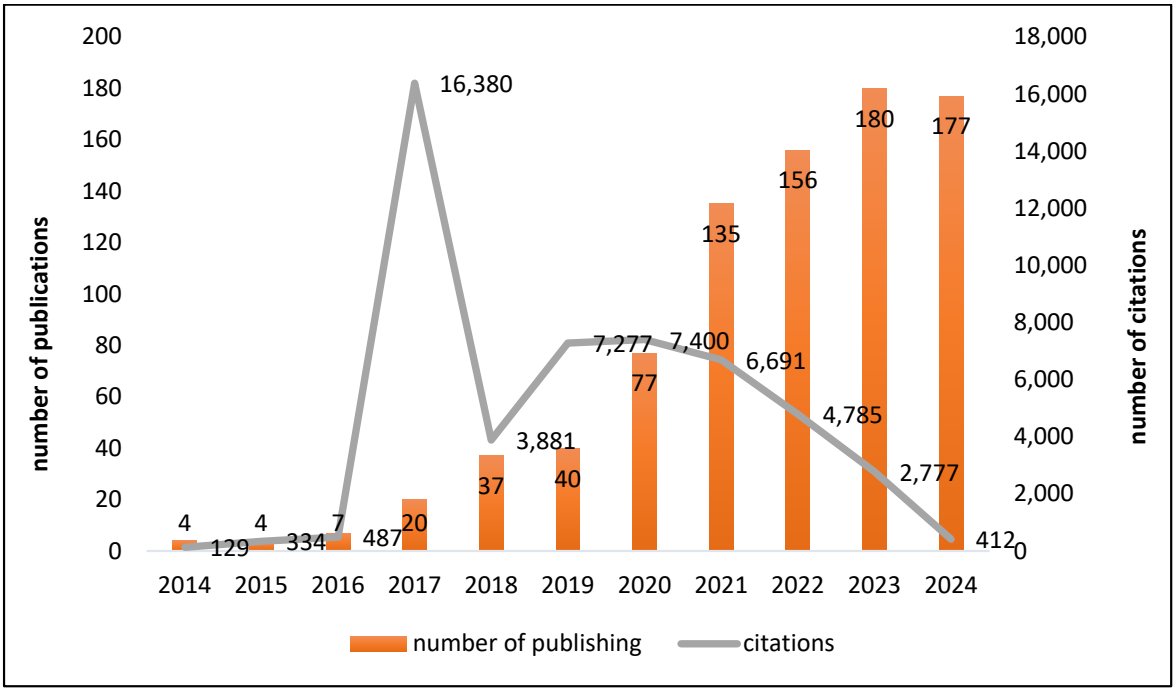



**Figure 3.** Number of citations and publications per year from 2014 to 2024 in Scopus.

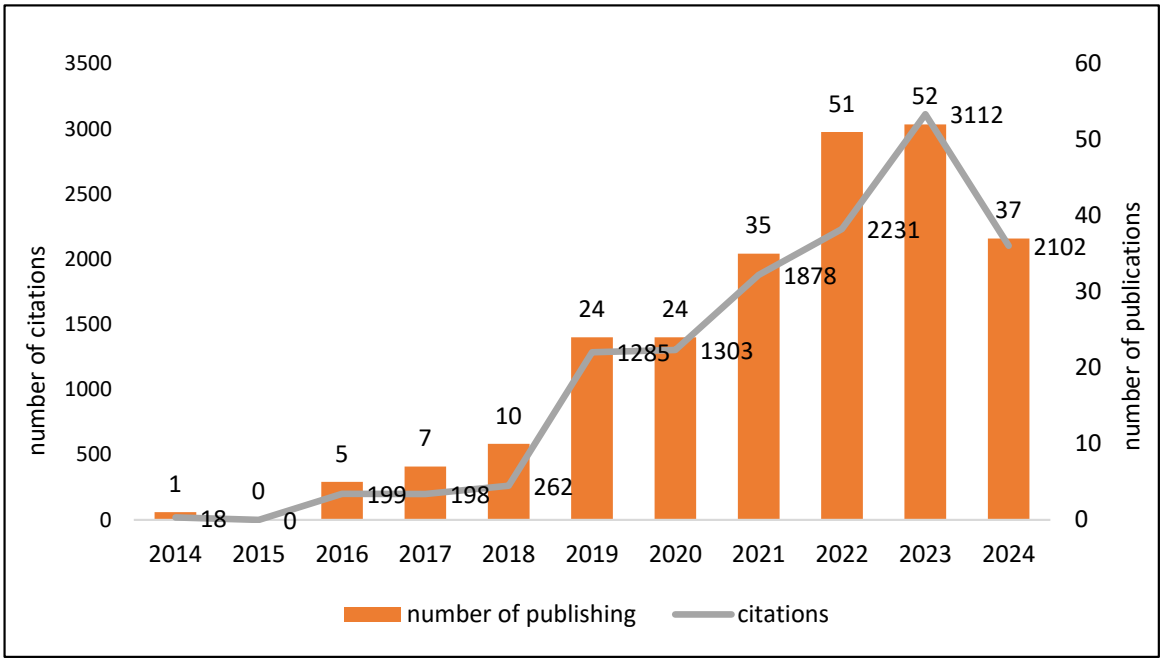



**Figure 4.** Number of citations and publications per year from 2014 to 2024 in Web of Science.

The abnormal rise in citation trends observed in Figure 2 can be attributed to the influence of several highly cited research papers published in 2018 and 2019. Notably, studies such as Wang et al. (2018) [12], which introduced advancements in interactive medical image segmentation using deep learning with image-specific fine-tuning, and Mallick et al. (2019) [13], who developed a deep wavelet autoencoder-based approach for brain MRI cancer detection, significantly contributed to the spike in citations.

Additional works by Hossain et al. (2019) [14] and Hemanth et al. (2019) [15] on brain tumor detection using convolutional neural networks and machine learning approaches further fueled this sharp increase, reflecting a surge in interest and acknowledgment of these impactful studies.

For Figure 3, the abnormal increase in citations can be attributed to the influence of highly cited research papers, particularly the comprehensive survey by Litjens et al. (2017) [16], titled "A Survey on Deep Learning in Medical Image Analysis". This foundational work provided an extensive overview of deep learning advancements in medical imaging and became a critical reference for subsequent studies in the field. Its widespread citation underscores the survey's pivotal role in shaping research directions and methodologies, leading to the marked rise in citation counts observed in Scopus.

The figures illustrate a consistent upward trend in citations and publications from 2014 to 2024 across IEEE, Scopus, and Web of Science. This steady increase highlights the growing relevance and research interest in artificial neural network (ANN) applications for segmentation tasks, with notable growth in recent years. The patterns depicted emphasize the broader academic community's engagement and the significant impact of ANN advancements on segmentation research, reflecting the field's evolving influence and importance in scientific literature.

### *3.3. AI Techniques Used in Brain Tumor Classification*

This subsection provides a detailed analysis of the AI techniques applied in the reviewed literature for brain tumor classification tasks. The findings, illustrated in Figures 5–9, reveal a predominant use of various AI methods.

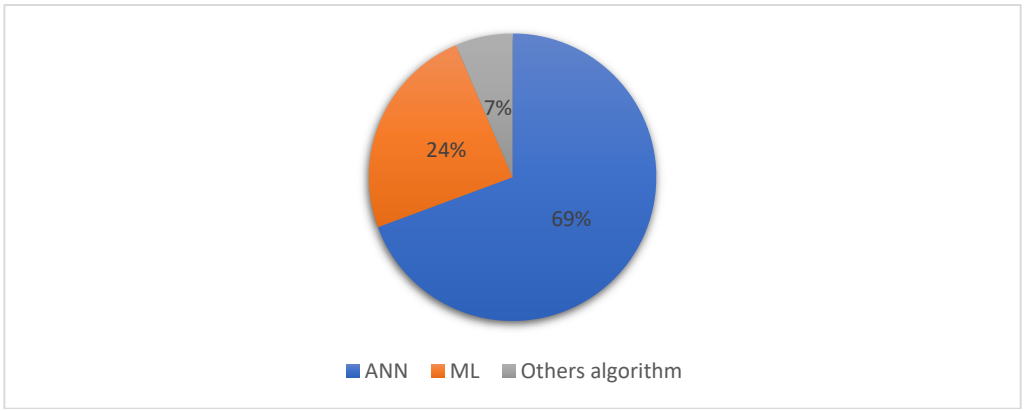



**Figure 5.** Type of ANN.

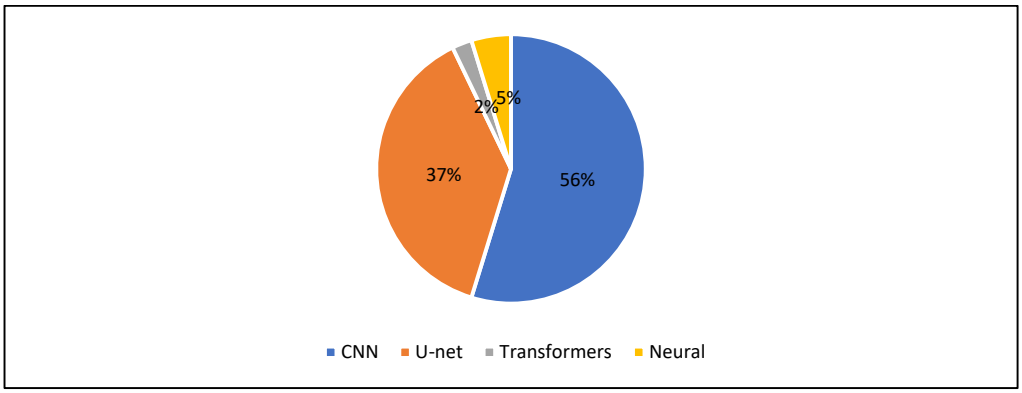



**Figure 6.** Neural network types.

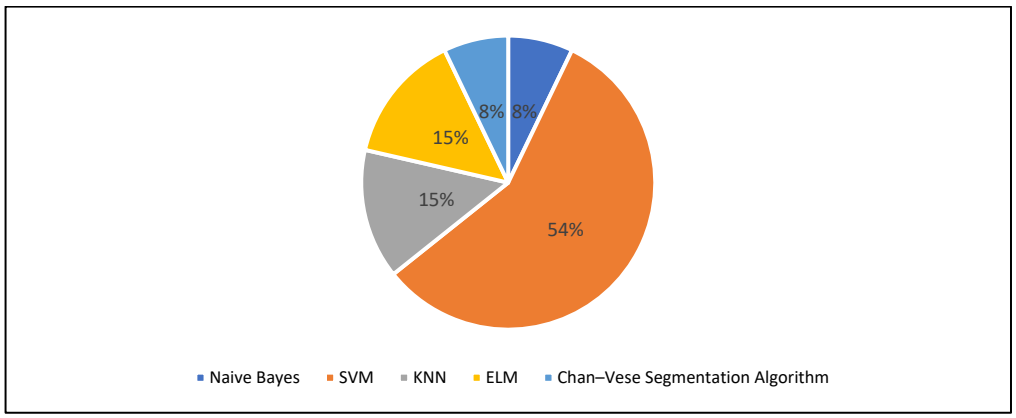



**Figure 7.** Machine learning types (supervised learning).

Figure 5 presents the overall distribution of AI techniques, indicating that neural networks account for 69% of all approaches. Among these, convolutional neural networks (CNNs) are the most widely utilized, as depicted in Figure 6 (56%), followed by U-Net (37%) and transformers (2%).

Figure 7 details machine learning methods, highlighting supervised learning techniques, such as naïve Bayes, support vector machines (SVM), and k-nearest neighbors (KNN). SVMs contribute 54% to the supervised learning category, followed by KNN (15%) and extreme learning machine (ELM) (15%).

Unsupervised techniques, shown in Figure 8, include K-means and fuzzy c-means (FCM) clustering, each representing 50% of the methods.

Figure 9 presents the usage of other algorithms, such as generative adversarial networks (GANs) and adversarial networks like MTANS, which represent emerging trends but are less frequently applied.

This comprehensive analysis underscores the diversity and evolution of AI methodologies in advancing brain tumor classification.

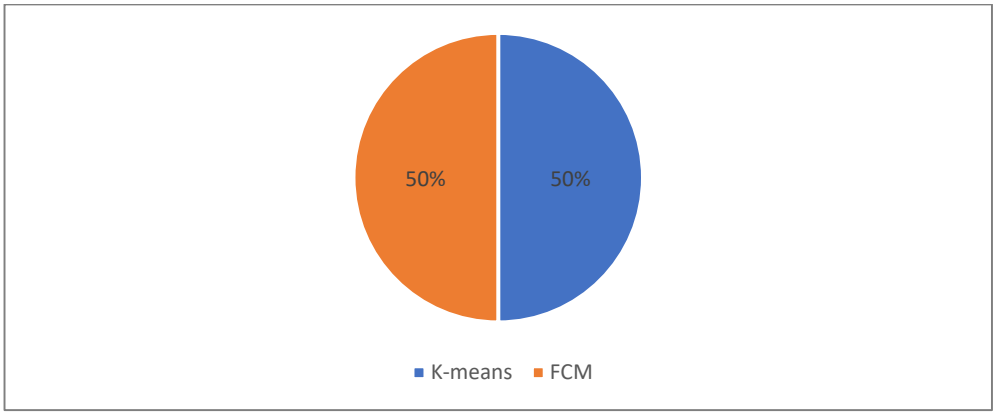



**Figure 8.** Machine learning types (unsupervised learning).

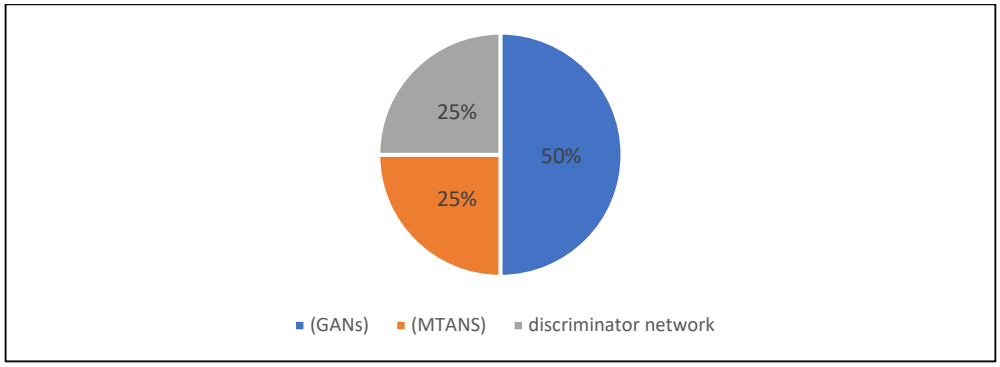



**Figure 9.** Other algorithms used in BTC.

### *3.4. Dataset Analysis*

After examining AI techniques, this subsection explores the types of datasets used in the reviewed studies. As depicted in Figure 10, the analysis reveals that 13 datasets were sourced from hospitals, emphasizing real-world medical data for developing and validating AI models. Among these databases that were used in the articles are as follows: Tianjin Universal Center of Medical Imaging and Diagnostic (TUCMD), Seoul National University Hospital, and The Cancer Imaging Archive, covering more than 2000 patients from over 200 institutions. In contrast, 38 datasets were obtained from publicly available repositories, such as Kaggle (BRATS 2013, BRATS 2014, BRATS 2015, BRATS 2016, BRATS 2019, BTD20, BraTS dataset, BraTS 2017, BraTS 2018, BraTS 2021, FigShare, SARTAJ, and Br35H). The databases covered different ages, from newborns to adults, as well as different types of tumors, highlighting the accessibility and utility of internet-based data resources.

This dataset analysis underscores the importance of diverse and comprehensive data in advancing brain tumor research.

In addition to model-related challenges, computational issues within datasets also pose significant barriers. These include the need for extensive data cleaning to address noise, labeling errors, and format inconsistencies. Missing data are another common issue that can affect model training and evaluation. Furthermore, large dataset volumes require substantial computational resources for storage, processing, and training, which may not

be accessible in all research settings. These challenges must be addressed to ensure reliable and scalable model development.

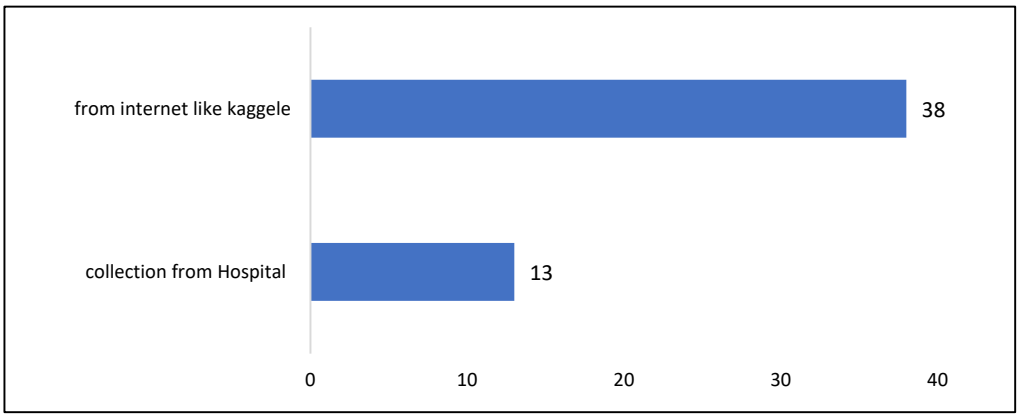



**Figure 10.** Dataset sources in tumor classification research.

### *3.5. Segmentation Approaches*

This subsection provides an overview of the segmentation approaches used in brain tumor classification, as presented in Figure 11. The analysis reveals that ANNs are the most widely adopted, accounting for 47% of all segmentation techniques. Within this category, commonly used approaches include CNNs, U-Net, context-guided attentive conditional random fields (CRFs), transformers, and the NeuroXAI framework.

Machine learning approaches constitute 18% of the segmentation methods. Several algorithms are employed, such as fuzzy c-means clustering, K-means clustering, and GANs.

The remaining 34% of approaches fall under "Other Techniques". These include essential image processing methods such as image normalization, feature extraction, filtering and denoising, edge detection, and mathematical transformations. These techniques are crucial for preparing and refining medical images.

This distribution underscores the dominant role of ANNs while highlighting the complementary use of machine learning and image processing techniques in brain tumor segmentation research.

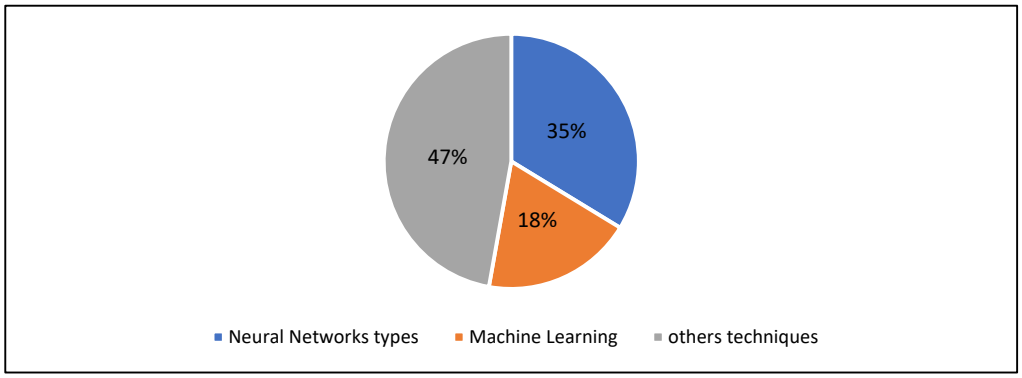



**Figure 11.** Distribution of segmentation techniques used in tumor classification studies.

### *3.6. Literature Classification*

A comprehensive qualitative analysis was conducted in response to the first research question. The following subsections describe the steps taken to complete this analysis.

#### 3.6.1. Classification of Articles into "Conceptual Contribution" and "Practical Contribution" Groups

Each article was classified as either a "conceptual contribution" or a "practical contribution".

- A conceptual contribution refers to research that involves description, comparison, analysis, or review-based studies on the topic;
- A practical contribution indicates that the research involved designing, developing, or implementing a program or presenting a novel algorithm.

This study includes 53 research papers, analyzed based on their research methodology. The articles were categorized as either conceptual or practical contributions, as shown in Table 3, which presents the classification of the 53 articles.

**Table 3.** Article classification.

| No. | Authors | Approach | Type |
|---|---|---|---|
| 1 | Díaz-Pernas et al., 2021 [17] | CNN, sliding mechanism | Practical |
| 2 | Ghafourian et al., 2023 [18] | Social spider optimization (SSO) algorithm | Practical |
| 3 | Menze et al., 2021 [19] | U-Net, intensity normalization, spatial harmonization | Conceptual |
| 4 | Kurdi et al., 2023 [20] | Fuzzy c-means clustering | Practical |
| 5 | Vankdothu & Hameed, 2022 [5] | K-means clustering, gray level co-occurrence matrix (GLCM) | Practical |
| 6 | Daimary et al., 2020 [21] | CNN, U-Net | Practical |
| 7 | Reddy et al., 2018 [22] | K-means clustering | Practical |
| 8 | Ramalakshmi et al., 2024 [23] | Gray standard normalization, regional binary patterns | Practical |
| 9 | Pereira et al., 2016 [24] | CNN, intensity normalization, bias field correction | Practical |
| 10 | Balamurugan & Gnanamanoharan, 2023 [25] | Hybrid FCM-GMM (fuzzy c-means and Gaussian mixture model) | Practical |
| 11 | Liu et al., 2021 [26] | U-Net, context-guided attentive CRFs | Practical |
| 12 | Lin et al., 2023 [27] | Modality-correlated cross-attention (MCCA), trans and CNN feature calibration (TCFC), transformer | Practical |
| 13 | Al-Masni & Kim, 2021 [28] | U-Net, inversion recovery (IR) | Practical |
| 14 | Zhang et al., 2021 [29] | GANS for knowledge transfer, cross-modality feature transition (CMFT) process, modalities, and a cross-modality feature fusion (CMFF) | Practical |
| 15 | Xu et al., 2023 [30] | Primary feature conservation (PFC) strategy and compact split-attention (CSA) | Practical |
| 16 | Peng et al., 2022 [31] | 3d U-Net | Practical |
| 17 | Ladkat et al., 2022 [32] | 3D attention U-Net, a mathematical model for pixel enhancement | Practical |
| 18 | Preetha et al., 2021 [33] | CNN | Practical |
| 19 | Xu et al., 2022 [34] | CNN, transformer | Practical |
| 20 | Telrandhe et al., 2016 [35] | K-means clustering, median filtering, and skull masking | Practical |
| 21 | Abd El Kader et al., 2021 [36] | CNN | Practical |
| 22 | Zeineldin et al., 2022 [37] | Neuroxai framework | Conceptual |
| 23 | Micallef et al., 2021 [38] | U-Net | Practical |

**Table 3.** *Cont.*

| No. | Authors | Approach | Type |
|---|---|---|---|
| 24 | Athisayamani et al., 2023 [39] | Canny Mayfly algorithm (ACMA), spatial gray level dependence matrix (SGLDM) | Practical |
| 25 | Choi et al., 2021 [40] | CNN | Practical |
| 26 | Hu et al., 2021 [41] | HPU-Net, fuzzy c-means clustering | Practical |
| 27 | Conte et al., 2021 [42] | U-Net | Practical |
| 28 | Khan et al., 2022 [43] | CNN | Practical |
| 29 | Archana & Komarasamy, 2023 [44] | U-Net | Practical |
| 30 | Zhang et al., 2020 [45] | Context residual module, inter-slice context information | Practical |
| 31 | Gunasekara et al., 2021 [46] | CNN, Chan–Vese algorithm | Conceptual |
| 32 | Anantharajan et al., 2024 [47] | Fuzzy c-means clustering, adaptive contrast enhancement algorithm (ACEA), and a median filter | Practical |
| 33 | Chen et al., 2021 [48] | Teacher model with adversarial learning, signed distance maps (SDM) | Practical |
| 34 | Gumaei et al., 2019 [49] | The paper does not focus on image segmentation but utilizes a principal component analysis-normalized GIST (PCA-NGIST) feature extraction method without segmentation. | Practical |
| 35 | Jia & Chen, 2020 [50] | FAHS-SVM, skull stripping, morphological operations, and wavelet transformation | Practical |
| 36 | MS Ullah et al. (2024) [51] | ResNet-50 and Stacked Autoencoders | Practical |
| 37 | Tripathy et al., 2023 [52] | Cropping and converting to grayscale, the binary thresholding method | Practical |
| 38 | Srinivasan S et al., 2024 [53] | Deep Convolutional Neural Network (CNN) | Practical |
| 39 | Tahir et al., 2019 [54] | Otsu method wavelet denoising and histogram equalization | Practical |
| 40 | Wadhwa et al., 2019 [55] | The paper reviews multiple approaches, focusing on a hybrid model combining fully convolutional neural networks (FCNN) with conditional random fields (CRF) | Conceptual |
| 41 | Farchi, 2023 [56] | The paper focuses on classification, not segmentation, but employs image preprocessing techniques such as resizing, grayscale conversion, image smoothing, and enhancement prior to classification | Practical |
| 42 | Chaudhary et al., 2020 [57] | Binary segmentation | Practical |
| 43 | Ramamoorthy et al., 2022 [58] | Otsu method | Practical |
| 44 | Kiranmayee et al., 2016 [59] | Fuzzy c-means clustering, thresholding method, Watershed segmentation | Practical |
| 45 | Lavanya & Nagasundaram, 2023 [60] | Filters | Practical |
| 46 | Harish & Ahammed, 2019 [61] | The segmentation aspect is not the focus of the paper. Instead, it discusses image enhancement techniques to improve the quality of brain MRI images | Practical |
| 47 | Poornachandra & Naveena, 2017 [62] | N4ITK algorithm | Conceptual |

**Table 3.** *Cont.*

| No. | Authors | Approach | Type |
|---|---|---|---|
| 48 | Archa & Kumar, 2018 [63] | CNN, wavelet transform, median filtering | Practical |
| 49 | Ali et al., 2022 [64] | U-Net, Markov random field (MRF) | Practical |
| 50 | Russo et al., 2022 [65] | CNN, transforming Cartesian coordinates into spherical coordinates | Practical |
| 51 | Biratu et al., 2021 [66] | CNN | Conceptual |
| 52 | Kapoor & Thakur, 2017 [67] | K-means clustering, Fuzzy C-Means clustering, Genetic Algorithms, thresholding method, Watershed segmentation | Conceptual |
| 53 | Aggarwal et al., 2023 [68] | Resnet | Practical |

The practical contribution category represents the majority, with 47 articles, while the conceptual contribution category consists of only six studies. This suggests that researchers focus more on developing practical applications than conceptual or theoretical discussions.

#### 3.6.2. Separating Articles That Address Segmentation

After classifying the articles, those specifically focused on brain tumor segmentation were identified, as this was a key aspect of the second research question. The selection process involved examining each article's title, abstract, and methodology.

As a result, 43 out of 53 articles were selected for further analysis. Figure 12 illustrates the percentage of articles focused on brain tumor segmentation compared to those addressing other research topics.

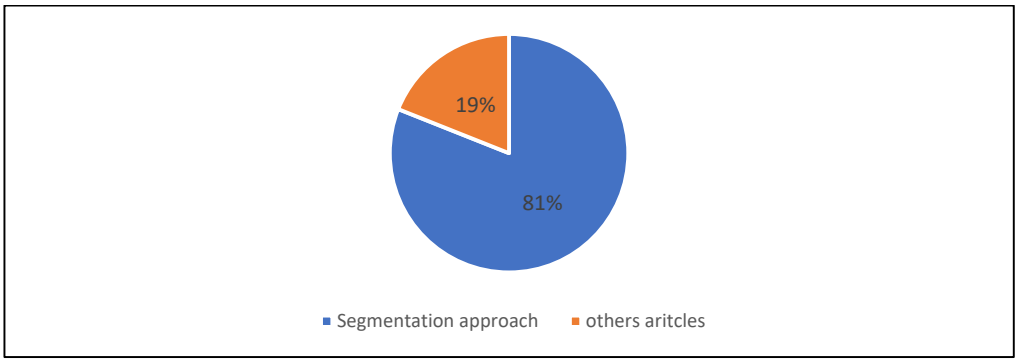



**Figure 12.** Distribution of articles on brain tumor segmentation vs. other research topics.

#### 3.6.3. Studying the Train/Test Mechanism, Evaluation Metrics, and Segmentation Approaches

At this stage, the articles focused on brain tumor segmentation were examined. The primary focus was training and testing techniques, evaluation metrics, and segmentation approaches. These aspects were extracted from the abstracts and methodologies of the selected studies.

The findings reveal various training and testing methods, as well as different evaluation metrics, depending on the role of segmentation. These results are summarized in Table 4.

**Table 4.** Summary of training/testing techniques, evaluation metrics, and segmentation approaches in brain tumor segmentation studies.

| No. | Authors | TT Mechanism | Evaluation Metrics | Segmentation Approach |
|---|---|---|---|---|
| 1 | Díaz-Pernas et al., 2021 [17] | Split 80-20, cross-validation method | DICE score, predicted tumor type accuracy score, and sensitivity | CNN, sliding mechanism |
| 2 | Ghafourian et al., 2023 [18] | Split 70-30, cross-validation method | Accuracy, sensitivity, specificity, F1 score | Social spider optimization (SSO) algorithm |
| 3 | Menze et al., 2021 [19] | Augmentation | Hausdorff distance, volumetric mismatch | U-Net, intensity normalization, spatial harmonization |
| 4 | Kurdi et al., 2023 [20] | MATLAB TOOL, | Pixel accuracy, accuracy, sensitivity, specificity, error rate | Fuzzy c-means clustering |
| 5 | Vankdothu & Hameed, 2022 [5] | Split 70-30 | DICE score, accuracy, Sensitivity, specificity | K-means clustering, Gray level co-occurrence matrix (GLCM) |
| 6 | Daimary et al., 2020 [21] | Split 60-40 | DICE score, accuracy | CNN, U-Net |
| 7 | Reddy et al., 2018 [22] | | DICE score, accuracy, precision, recall, true positive (TP), true negative (TN), false positive (FP), false negative (FN) | K-means clustering |
| 8 | Ramalakshmi et al., 2024 [23] | | False classification ratio, accuracy, Sensitivity, specificity | Gray standard normalization, regional binary patterns |
| 9 | Pereira et al., 2016 [24] | Cross-validation method | DICE score, Sensitivity, Positive Predictive Value (PPV) | CNN, intensity normalization, bias field correction |
| 10 | Balamurugan & Gnanamanoharan, 2023 [25] | Split 70-30 | Accuracy, sensitivity, specificity, precision, recall, F-score, DICE Similarity Index (DSI) | Hybrid FCM-GMM (fuzzy c-means and Gaussian mixture model) |
| 11 | Liu et al., 2021 [26] | Cross-validation method | Sensitivity, specificity, Hausdorff 95 distance | U-Net, context-guided attentive CRFs |
| 12 | Lin et al., 2023 [27] | Split 80-10-10 | DICE score, sensitivity, Hausdorff 95 distance | Modality-correlated cross-attention (MCCA), Trans and CNN feature calibration (TCFC), transformer |
| 13 | Al-Masni & Kim, 2021 [28] | Split 80-20 | DICE score, accuracy, sensitivity, specificity, Jaccard index, Matthews correlation coefficient (MCC), and area under the curve (AUC) | U-Net, inversion recovery (IR) |
| 14 | Zhang et al., 2021 [29] | Split 80-20 | DICE, score, sensitivity, specificity, Hausdorff 95 distance | Gans for knowledge transfer, cross-modality feature Transition (CMFT) process, modalities, and a cross-modality feature fusion (CMFF) |
| 15 | Xu et al., 2023 [30] | Split 70-10-20, augmentation, Adam optimization | DICE score, accuracy, precision, recall, mean intersection over union (MIOU) | Primary feature conservation (PFC) strategy and compact split-attention (CSA) |
| 16 | Peng et al., 2022 [31] | Split 80-20, augmentation | DICE score, ICC | 3D U-Net |
| 17 | Ladkat et al., 2022 [32] | Split 77-23 | Sensitivity, specificity, Hausdorff95 distance | 3D attention U-Net, a mathematical model for pixel enhancement |

**Table 4.** *Cont.*

| No. | Authors | TT Mechanism | Evaluation Metrics | Segmentation Approach |
|---|---|---|---|---|
| 18 | Preetha et al., 2021 [33] | Split 8-0-20, cross-validation method | Dice score, C-index, SSIM | CNN |
| 19 | Xu et al., 2022 [34] | Adam optimization | Hausdorff 95 distance, mean Intersection over union (MIOU) | CNN, transformer |
| 20 | Telrandhe et al., 2016 [35] | SVM | Accuracy | K-means clustering, median filtering, and skull masking |
| 21 | Abd El Kader et al., 2021 [36] | Split 8-0-20, cross-validation method | DICE score, accuracy, sensitivity, specificity, F1 score, precision | CNN |
| 22 | Zeineldin et al., 2022 [37] | Augmentation, Z-score | DICE score | Neuroxai framework |
| 23 | Micallef et al., 2021 [38] | Split 80-20, cross-validation method, augmentation | DICE score, sensitivity, specificity, Hausdorff95 distance | U-Net |
| 24 | Athisayamani et al., 2023 [39] | Split 70-15-15, augmentation | Accuracy, sensitivity, specificity, and recall | Canny Mayfly algorithm (ACMA), spatial gray level dependence matrix (SGLDM) |
| 25 | Choi et al., 2021 [40] | | Accuracy, precision, and recall | CNN |
| 26 | Hu et al., 2021 [41] | Cross-validation method | DICE score, Jaccard coefficient | HPU-Net, fuzzy c-means clustering |
| 27 | Conte et al., 2021 [42] | Split 64-20-16, cross-validation method | DICE score | U-Net |
| 28 | Khan et al., 2022 [43] | Split 87-13, cross-validation method | Accuracy, error rate | CNN |
| 29 | Archana & Komarasamy, 2023 [44] | Split 80-20 | DICE score, accuracy, F1 score, precision, recall | U-Net |
| 30 | Zhang et al., 2020 [45] | Split 75-0-25, cross-validation, augmentation | Hausdorff95 distance | Context residual module, inter-slice context information |
| 31 | Gunasekara et al., 2021 [46] | Split 80-0-20, cross-validation | DICE score, peak signal-to-noise ratio | CNN, Chan–Vese algorithm |
| 32 | Anantharajan et al., 2024 [47] | SVM | Accuracy, sensitivity, specificity, peak signal-to-noise ratio, Jaccard coefficient (JC) | Fuzzy c-means clustering, Adaptive Contrast Enhancement Algorithm (ACEA), and a median filter |
| 33 | Chen et al., 2021 [48] | Split 80-0-20, cross-validation method | False positive rate (FPR), true positive rate, positive predictive value (PPV) | Teacher model with adversarial learning, signed distance maps (SDM) |
| 34 | Jia & Chen, 2020 [50] | SVM | Accuracy, sensitivity, specificity | FAHS-SVM, skull stripping, morphological operations, and wavelet transformation |

**Table 4.** *Cont.*

| No. | Authors | TT Mechanism | Evaluation Metrics | Segmentation Approach |
|---|---|---|---|---|
| 35 | Tripathy et al., 2023 [52] | Split 67-13-20 | DICE score, accuracy, sensitivity, specificity, F1 score, precision | Cropping and converting to grayscale, binary thresholding |
| 36 | Srinivasan S et al., 2024 [53] | 5-fold cross-validation Dataset split into 60 training, 20 validation, 20 testing | Accuracy, Sensitivity, Specificity, Precision, ROC-AUC | classification task only (binary, multi-type, and tumor grade) |
| 37 | Tahir et al., 2019 [54] | Split 90-0-10, cross-validation method, SVM | Accuracy, sensitivity, specificity | Wavelet denoising and histogram equalization |
| 38 | Ramamoorthy et al., 2022 [58] | | Accuracy, specificity, precision | Otsu method |
| 39 | Kiranmayee et al., 2016 [59] | SVM | DICE score, accuracy | Fuzzy c-means clustering, thresholding method, Watershed segmentation |
| 40 | Archa & Kumar, 2018 [63] | Augmentation | DICE score, accuracy | CNN, wavelet transform, median filtering |
| 41 | Ali et al., 2022 [64] | | Accuracy, sensitivity, precision | UNET, Markov Random Field (MRF) |
| 42 | Russo et al., 2022 [65] | Split 80-20, cross-validation method, augmentation | DICE score, sensitivity, specificity, Hausdorff 95 distance | CNN, transforming Cartesian coordinates to spherical coordinates, Canny |
| 43 | Aggarwal et al., 2023 [68] | Split 34-46 | Sensitivity, specificity, Jaccard coefficient, peak signal-to-noise ratio, mean square error (MSE) | Resnet |

## 4. Discussion

The review reveals that practical contributions dominate the field, with 47 studies focusing on practical applications, compared to only six studies classified as conceptual contributions. This trend highlights a strong inclination among researchers over the past decade toward advancing practical aspects of the field rather than theoretical frameworks.

Furthermore, this review identified two pivotal works [32,44] that introduced groundbreaking methods widely recognized as innovations. These studies have garnered substantial citations, underscoring their significant impact and contributions to the field.

The training and testing mechanisms discussed in this review incorporate various methods and techniques. The most frequently used approach is the one-split method, employed in 26 papers. This method involves dividing the dataset into two parts, typically allocating the majority for training and the remainder for testing (e.g., 80–20% or 70–30% splits). Dataset size and model complexity often determine the split ratio.

The second most common approach is data augmentation, which has been applied in 20 papers to increase dataset size and diversity by introducing transformations to the existing data. The validation technique, used in 14 papers, divides datasets into three parts for training, validation, and testing.

Additional techniques include the following:

- Support vector machines (SVM), noted in five papers;
- MATLAB, Keras, and Z-score normalization.

These methods were employed in 43 papers that utilized segmentation approaches to evaluate model performance. This review highlights the popularity of techniques such as dataset splitting, augmentation, and validation. They are essential steps in deep learning workflows, each with specific advantages and limitations. Splitting the dataset into training, validation, and test sets helps assess model performance objectively, but improper splitting may lead to biased results. Data augmentation enhances model generalization by creating diverse samples from limited data; however, excessive or unrealistic transformations can introduce noise. Validation techniques, such as cross-validation, improve reliability but increase computational cost. A balanced approach is required to ensure robust and meaningful model evaluation, which is widely adopted for its effectiveness in improving results.

The evaluation metrics summarized in Table 5 demonstrate the diversity of approaches used to assess model performance. The DICE score and accuracy are indeed popular metrics because of their straightforward application and ability to provide immediate insights into model performance. Among these, the accuracy score, cited in 25 papers, measures the ratio of correctly identified instances (true positives and true negatives) relative to the total number of instances. The DICE score, used in 23 papers, evaluates the overlap between predicted and actual sets, making it a crucial metric for image segmentation and binary classification tasks. Sensitivity, sometimes referred to as recall, measures the proportion of actual positives that are correctly identified by the model. Specificity measures the proportion of actual negatives that are accurately identified as such, thus avoiding false positives. F1-score is the harmonic mean of precision (the number of true positive results divided by the number of all positive results, including those not relevant) and recall.

**Table 5.** Distribution of metrics in the articles.

| No. | Authors | Accuracy | Sensitivity | Specifity | Recall OR (TPR) | F1 Score | Precision OR (ppv) | Dice Score | Hausdorff 95 Distance | Other Classification Metrics | Other Segmentation Metrics |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Díaz-Pernas et al., 2021 [17] | X | X | | | | | X | | | |
| 2 | Ghafourian et al., 2023 [18] | X | X | X | | X | | | | | |
| 3 | Menze et al., 2021 [19] | | | | | | | | | | X |
| 4 | Kurdi et al., 2023 [20] | X | X | X | | | | | | X | X |
| 5 | Vankdothu & Hameed, 2022 [5] | X | X | X | | | | X | | | |
| 6 | Daimary et al., 2020 [21] | X | | | | | | X | | | |
| 7 | Reddy et al., 2018 [22] | X | | | X | | X | X | | X | |
| 8 | Ramalakshmi et al., 2024 [23] | X | X | X | | | | | | X | |
| 9 | Pereira et al., 2016 [24] | | X | | | | X | X | | | |
| 10 | Balamurugan & Gnanamanoharan, 2023 [25] | X | X | X | X | X | X | X | | | |
| 11 | Liu et al., 2021 [26] | | X | X | | | | | X | | |
| 12 | Lin et al., 2023 [27] | | X | X | | | | | X | | |

**Table 5.** *Cont.*

| No. | Authors | Accuracy | Sensitivity | Specifity | Recall OR (TPR) | F1 Score | Precision OR (ppv) | Dice Score | Hausdorff 95 Distance | Other Classification Metrics | Other Segmentation Metrics |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 13 | Al-Masni & Kim, 2021 [28] | X | X | X | | | | X | | X | |
| 14 | Zhang et al., 2021 [29] | | X | X | | | | X | X | | |
| 15 | Xu et al., 2023 [30] | X | | | X | | X | X | | | X |
| 16 | Peng et al., 2022 [31] | | | | | | | X | | | X |
| 17 | Ladkat et al., 2022 [32] | | X | X | | | | | X | | |
| 18 | Preetha et al., 2021 [33] | | | | | | | X | | X | X |
| 19 | Xu et al., 2022 [34] | | | | | | | | X | | X |
| 20 | Telrandhe et al., 2016 [35] | X | | | | | | | | | |
| 21 | Abd El Kader et al., 2021 [36] | X | X | X | | X | X | | | | |
| 22 | Zeineldin et al., 2022 [37] | | | | | | | X | | | |
| 23 | Micallef et al., 2021 [38] | | X | X | | | | X | X | | |
| 24 | Athisayamani et al., 2023 [39] | X | X | X | X | | | | | | |
| 25 | Choi et al., 2021 [40] | X | | | X | | X | | | | |
| 26 | Hu et al., 2021 [41] | | | | | | | X | | | X |
| 27 | Conte et al., 2021 [42] | | | | | | | X | | | |
| 28 | Khan et al., 2022 [43] | X | | | | | | | | X | |
| 29 | Archana & Komarasamy, 2023 [44] | X | | | X | X | X | X | | | |
| 30 | Zhang et al., 2020 [45] | | | | | | | | X | | |
| 31 | Gunasekara et al., 2021 [46] | | | | | | | X | | | X |
| 32 | Anantharajan et al., 2024 [47] | X | X | X | | | | | | | X |
| 33 | Chen et al., 2021 [48] | | | | X | | X | | | X | |
| 34 | Jia & Chen, 2020 [50] | X | X | X | | | | | | | |
| 35 | Tripathy et al., 2023 [52] | X | X | X | | X | X | X | | | |
| 36 | Srinivasan S et al., 2024 [53] | X | X | X | | | X | | | X | |
| 37 | Tahir et al., 2019 [54] | X | X | X | | | | | | | |
| 38 | Ramamoorthy et al., 2022 [58] | X | | X | | | X | | | | |
| 39 | Kiranmayee et al., 2016 [59] | X | | | | | | X | | | |
| 40 | Archa & Kumar, 2018 [63] | X | | | | | | X | | | |
| 41 | Ali et al., 2022 [64] | X | X | | | | X | | | | |
| 42 | Russo et al., 2022 [65] | | X | X | | | | X | X | | |
| 43 | Aggarwal et al., 2023 [68] | | X | X | | | | | | X | X |

Additional metrics such as true positives (TP), true negatives (TN), false positives (FP), false negatives (FN), false positive rate (FPR), negative predictive value (NPV), boundary displacement error (BDE), mean intersection over union (mIoU), false classification rate, pixel accuracy, mismatch, volumetric overlap, Matthews correlation coefficient (MCC), and

area under the curve (AUC) further illustrate the wide range of evaluation methods utilized in the literature.

The variety of evaluation metrics reflects the demands of different tasks and datasets. While accuracy remains a widely used metric, its limitations in addressing imbalanced datasets necessitate supplementary measures such as sensitivity, specificity, and F1 score for a more comprehensive analysis. In image segmentation tasks, metrics like the DICE score, Jaccard coefficient, and Hausdorff95 distance provide deeper insights into model performance. Domain-specific metrics such as PSNR and MSE are also critical in evaluating image quality in relevant contexts.

The selection of appropriate metrics should align with the research objectives, dataset characteristics, and application requirements to ensure thorough and meaningful assessments of model efficacy.

GANs, while powerful generative models, have faced several criticisms that can limit their practical application, especially when compared to more established architectures like CNNs and U-Nets for specific tasks like image segmentation.

Emerging techniques like federated learning and self-supervised learning hold significant promise in the realm of tumor classification, yet they remain relatively underexplored. Federated learning offers a solution to privacy concerns by allowing multiple institutions to collaboratively train models without the need to share sensitive patient data.

On the other hand, self-supervised learning is valuable in situations where annotated data are scarce. It allows models to extract meaningful patterns and representations from large volumes of unlabeled data.

## 5. Conclusions

This systematic review analyzed literature on image processing, particularly medical images, focusing on brain tumor detection using magnetic resonance imaging (MRI). Fifty-three articles from the past ten years were reviewed and selected for their relevance to brain tumor detection. The analysis showed that 43 of the 53 studies employed brain tumor segmentation techniques, and 47 included practical applications of their proposed methods. Most studies relied on convolutional neural networks (CNNs) and machine learning (ML) models. Neural networks are recognized for their strong learning ability and accuracy, but require large datasets. Fuzzy logic offers interpretability and handles uncertainty well, but may lack precision in complex patterns. Genetic algorithms are effective in feature selection and optimization, but are computationally intensive. By comparing these techniques, the review provides insights into their suitability for different tumor classification tasks.

However, several limitations were identified, including long training times for datasets, particularly in cases involving hybrid models or complex ML algorithms. Additionally, some studies had insufficient dataset sizes, limiting their ability to achieve optimal accuracy. These findings emphasize the need for further in-depth research to enhance accuracy, as the results directly impact patient outcomes. Therefore, several approaches can be adopted to enhance the model's accuracy when dealing with limited medical image data, like (data augmentation, transfer learning, synthetic data generation, and others).

Prioritizing tumor segmentation, localization, and classification remains critical to improving the precision and reliability of brain tumor detection methods. Future studies should explore larger, more diverse datasets and develop optimized computational strategies to mitigate processing inefficiencies. Additionally, integrating multi-modal imaging techniques and leveraging advanced AI models could drive significant breakthroughs in early tumor detection, ultimately leading to improved clinical decision-making and patient survival rates.

*Ethical Considerations*

While this study does not directly utilize patient data, it is essential to emphasize the ethical standards pertinent to research of this nature. Upholding patient privacy and adhering to data protection regulations like GDPR or HIPAA is a crucial obligation in clinical and health data research. The articles utilized for this study had obtained necessary ethical approval, ensuring compliance with institutional and regulatory guidelines. Any future work involving direct data collection will explicitly address obtaining ethical approvals as well as establishing protocols for handling such information.

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