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A Study of Brain Tumor detection using MRI images

Dr. Asadullah Kehar *, **Dr. Mashooque Ali Mahar**, **Mr. Shahid Hussain Danwar**
Ms. Sidra Parveen, **Ms. Maria Bhutto**, **Ms. Zoya Qutrio**

Institute of Computer Science, Shah Abdul Latif University, Khairpur, Sindh, Pakistan

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Abstract
This study investigates the advantages of an algorithm for detecting brain tumors using magnetic resonance imaging. The thematic analysis demonstrates how the algorithm can be understood and changed through narrative descriptions. The findings highlight areas for improvement, which aids in the direction of future research. Based on unexpected results, the algorithm was improved over time. Even though the study had some restrictions and limitations, this makes the algorithm a versatile tool for detecting brain tumors. This study is an important step toward better understanding algorithmic applications and demonstrates the significance of qualitative insights in shaping the future of brain tumor detection methods.

***Correspondence author email address:** asad.kehar@salu.edu.pk
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1 Introduction
Brain tumors are skull-based cancers. They can cause nerve damage or death, making them dangerous. Cancer can be aggressive or non-aggressive. This is significant and shows the gravity of the situation. Untreated cancer can kill. Because of this, addressing this threat immediately is crucial. Nobody can overstate the importance of treating brain tumors quickly for better outcomes. In both cases, early detection is crucial, [1] . Finding a patient quickly improves survival and makes it easier to administer the right medication. Early brain cancer detection allows doctors to use less invasive and less harmful treatments than radiation and surgery. Early treatment reduces symptoms and improves health. Patient quality of life and freedom improve over time. Identifying patients quickly is crucial to their health. This general rule applies to many situations.

1.1 Statement of the Problem
Despite advances in research, it is still difficult to tell if someone has brain cancer. This may be due to the complexity of these issues. The American Association of Neurological Surgeons stated in April 2019 that it was more difficult to detect and classify cancer because tumors did not all look the same in terms of size, location, and growth patterns [2] . When there are no symptoms, it can be difficult to determine whether or not a cancer is in its early stages. Diagnostic tech-

nology can be extremely useful, but it is not without flaws. CT scans may be able to detect some cancers as an alternative to traditional surgeries, which can be time-consuming and dangerous. Even though there are some issues [3] , the American Cancer Society believes that imaging with magnetic resonance imaging (MRI) is still the best way to detect cancer. The ability of magnetic resonance imaging (MRI) to show tumor features is useful for both detecting and treating tumors. Because it does not involve cutting into the body, magnetic resonance imaging (MRI) is a safer alternative to surgery. However, because MRI data analysis is highly subjective and requires a high level of skill, there is a chance that the results will not match and the conclusions will be incorrect.

1.2 Objectives of the Study

To achieve the study's two goals, much research was done because brain tumors are hard to find. First, the study examined brain cancer diagnosis and treatment methods and their pros and cons [4] . To assess its capabilities, the magnetic resonance imaging (MRI) machine was clinically tested. The main goal was to identify method flaws and areas for improvement. Besides the primary goal, the secondary goal was to test and improve MRI brain tumor detection. This innovative method combines machine learning and deep learning to teach. [5] tested the procedure several times to see how accurate, fast, selective, and comparable it was to other methods. Modern technology could help doctors diagnose and treat patients, according to the study. One part of the experiment improved patient outcomes, while another found new brain cancer detection methods.

2 Literature Review

2.1 Overview of Brain Tumor Detection Techniques

The way brain tumors are found has changed due to technological advances. Histopathology from biopsy sections has been the main method. However, it is invasive and can make mistakes, so we need faster and more automated methods. Recent advances in deep learning and convolutional neural networks have made brain tumor detection easier. Studies like

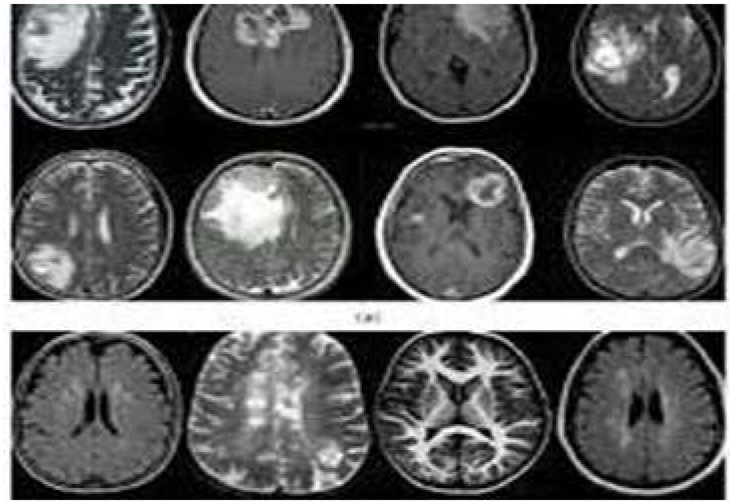

Figure 1. Source: MDPI

[6] suggest fully automated CNN multi-classification as an alternative to invasive histopathological analysis. [7] suggested hybrid CNN methods that use multiple MRI techniques and segmentation strategies to better detect complex gliomas. Automated deep learning methods improve early and accurate diagnoses, improving patient outcomes. Some brain MRI images are shown in Figure 1.

2.1.1 Traditional Methods

Standard brain tumor diagnosis methods like biopsy section histopathology have been around for a long time. While invasive, time-consuming, and error-prone methods are still issues, they have led people to seek better alternatives. The literature promotes automated methods to address these issues. This change highlights the importance of early and accurate brain tumor detection. This change acknowledges traditional methods' limitations and allows for more technologically advanced methods.

2.1.2 Recent Advancements

Deep learning, particularly CNNs, has changed the way brain tumors are discovered. A recently published study suggests using fully automated CNN multi-classification. Instead of invasive histopathological analysis, this method employs an automated method. These methods are generally accurate and may aid in early diagnosis. According to a study [8] , hybrid CNN methods can also help divide gliomas. To improve the accuracy of these methods, various types of magnetic resonance imaging (MRI), patch-based approaches, dropout regularization, and two-phase training are used. Because tumors are so complex, we require segmentation strategies that are both specific and general. Brain tumors may be easier to detect if threshold segmentation is used in conjunction with morphological operations. At the same time, these methods are useful for problems with fuzzy edges and odd shapes. These pre- and post-processing techniques may aid segmentation and reduce the number of false positives. Recent events have demonstrated that finding brain tumors is becoming increasingly automated and based on deep learning. According to Sultana [9] Jahan, researchers are using cutting-edge computers to achieve unprecedented levels of accuracy and speed. Because of this new era of neuroimaging and diagnostics, everything will be different. Early and accurate diagnosis can lead to better patient outcomes, and these methods are improving at the same rate as technology.

2.1.3 Role of MRI in Brain Tumor Detection

- **Strengths and Limitations** Since it allows doctors to see inside the brain without touching it, magnetic resonance imaging (MRI) is used to detect and study brain tumors. According to Bhattacharyya and Kim [10] , multiplanar imaging is better at contrasting soft tissues and providing a clear picture. They are listed in the preceding list of advantages. Because of this characteristic, it is easier to locate various parts of the brain and draw attention to problems such as tumors. The MRI employs various imaging sequences designed to examine various tissues. Type T1 images are mostly about anatomy, whereas type T2 images are mostly about disease. Contrast-enhanced images can reveal blood flow near tumors. This allows for a more in-depth examination of the brain's structure and problems. Magnetic resonance imaging (MRI) has some limitations [6] . They may be unable to remain still or fearful of being squeezed, resulting in poor image quality. Metal implants and other foreign bodies, as well as artifacts, can be placed in them. It's also critical to have the right radiologist skills to understand the results of magnetic resonance imaging (MRI), which adds to the variability.
- **Comparative Analysis with Other Imaging Techniques:** An MRI is superior to other imaging methods for detecting brain tumors. CT can detect new bleeding and bone problems, but it does not show soft tissue as well as MRI. It has been discovered that MRI is superior to PET for displaying anatomy [11] . Although PET can show how metabolism works, it may not be as accurate as an MRI. PET-MRI and other hybrid imaging methods have become more common in recent years. These methods combine the best aspects of both approaches to more accurately detect brain tumors. PET-MRI is one method. Hybrid systems, on the other hand, are difficult to find and expensive, which may explain why they aren't widely used. Unfortunately, due to the dense bone structure of the skull, ultrasound is less useful for detecting tumors within the skull. Ultrasound is typically used to detect tumors located outside of the head. Magnetic resonance imaging (MRI) is the best way to detect brain tumors because it works on multiple planes and does not show much contrast in soft tissues citeclevelandclinic2022 . Even though each type of imaging has advantages, this remains true. Magnetic resonance imaging (MRI) is becoming more effective at detecting brain tumors and will be able to do so more completely as hybrid imaging and MRI techniques improve.
- **Review of Existing Algorithms** Commonly Used Algorithms for MRI Image Analysis: Many algorithms have been used to aid pathology and extract useful information from brain tumors MRI images. Advanced computer techniques like machine learning and deep learning have changed this field. Traditional image processing methods have also been crucial [12] . Traditional image processing algorithms include

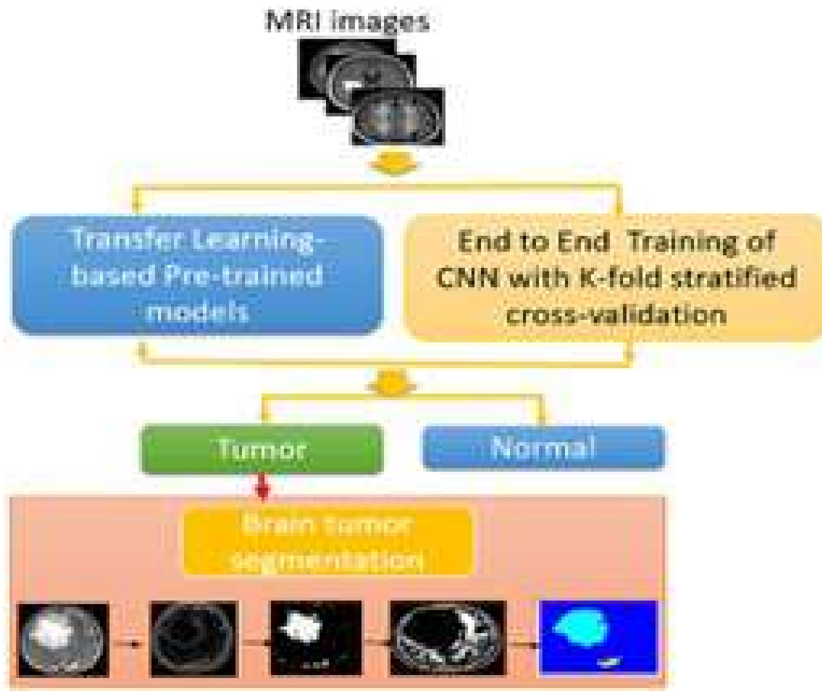

Figure 2. Source: Frontiers

thresholding, segmentation, and morphological operations. Thresholding can distinguish tumors from non-tumors based on intensity. Morphological operations improve segmented areas, while segmentation algorithms draw tumor edges. Machine learning algorithms are becoming more common. SVMs and Random Forests are the most popular. Support vector machines (SVMs) excel at binary classification, so they can distinguish tumors from non-tumors. Random Forests, an ensemble learning method, can handle large, complex datasets and produce good results [13] . Neuronal networks (CNN) and other deep learning algorithms are useful for MRI image analysis as shown in Figure 2. Many CNNs can automatically learn image feature hierarchies. This makes them ideal for difficult tasks like tumor detection. These networks can recognize complex patterns, making it easier to find abnormal tissue [14] .

- **Performance and Limitations of the Algorithms** However, the way these algorithms work is determined by both the characteristics of the dataset and the nature of the task. Traditional image processing algorithms, while fast and accurate, may be incapable of handling brain tumors due to their complexity and constant change. Changes in image intensity can have an impact on thresholding, resulting in less-than-ideal results [5] . Support Vector Machines and Random Forests can help find brain tumors more easily. Because feature engineering is so critical to their work, they may struggle with datasets that are both complex and diverse. Deep learning algorithms (CNNs) shine when it comes to MRI pattern recognition. These methods can be trusted, and they may work better in some situations than others. CNNs can only work with large datasets with a large number of labels. According to Sadad et al.[15] , CNNs are "black boxes," which means the results of their analysis are difficult to interpret. Although these algorithms have improved the accuracy of MRI image analysis, it is critical to understand what they cannot do. Many people are concerned about how to interpret the results, overfitting, and a lack of data. Researchers are developing a fast, accurate brain tumor detection method. One of their main goals.

3 Methodology

3.1 Data Collection

The study used MRI images from trusted medical databases and journals to ensure data accuracy. The dataset, which included many studies, showed how much brain imaging research has been done. Imaging techniques and resolution were carefully considered when assembling the dataset to handle neuroimaging's complexity. Researchers did extensive research before selecting studies and imaging sources. This produced many brain images. Unique features and details of each image were carefully recorded, adding depth and complexity to the dataset. The first studies' inclusion rules were written down to clarify and follow primary research methods.

3.1.1 Source of MRI Images

This investigation employed trustworthy medical databases and journal MRIs. Archives and past research yielded a huge and diversified set of brain MRI images that directly answered the research questions [16] . Data accuracy and reliability are guaranteed by this source.

3.2 Characteristics of the Dataset

The dataset showed brain imaging research's breadth with MRI images from various studies. Imaging methods and resolution were examined [15] . This comprehensive method was implemented after the research onion's "choices" layer, where careful dataset assembly decisions were made. Researchers carefully selected studies and imaging sources for brain image diversity. The images were then captured using various imaging methods and resolution formats. Each dataset image had unique features and information, adding complexity and depth. Initial study inclusion criteria were carefully documented to ensure clarity and primary research methods. Each image's details and characteristics were meticulously documented during dataset creation. The compilation used previous research [17] . The goal was to create a dataset that answers research questions and accounts for imaging study details and variations. The historical data collection method was crucial to future research. Thus, MRI images were trusted and significant.

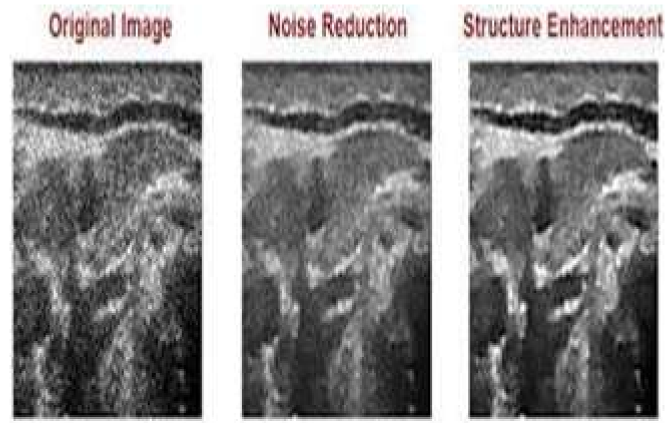

Figure 3. Source: ResearchGate

3.3 Preprocessing

Image improvement and noise reduction occur during preprocessing. This phase uses advanced contrast and noise reduction. Simplifying neuroimaging data is key. Standardizing image resolution was key. This requires extensive scaling or resampling for uniformity. Voxel sizes and spatial calibration were carefully studied to retain image resolution. Future comparisons were more accurate using the dataset. Standards and medical imaging rules were strictly followed throughout the process.

3.3.1 Image Enhancement and Noise Reduction

The crucial preprocessing phase improved MRI images. Advanced techniques like contrast adjustment and noise reduction were used as shown in Figure 3. Best interpretability was stressed because neuroimaging data is so complicated [18] . Contrast adjustment was crucial for highlighting tissue density differences and complex brain parenchyma structures. Maintaining a clear signal-to-noise ratio-maintained image diagnostic accuracy. While reducing noise, artifacts were skillfully removed.

3.3.2 Standardization of Image Resolution

During the preprocessing stage, one of the most important decisions was to ensure that all of the MRIs had the same image resolution. Because of this wise decision, the "choices" layer of the research onion had to undergo complex image resizing or resampling to achieve continuous resolution. This decision was made to achieve the goal [19] . It was discussed how important accuracy is in neuroimaging research, which made future comparisons easier. Looking back at these preprocessing efforts after the fact can help you understand how complicated medical imaging is. The voxel sizes and spatial calibration were critical for obtaining a good image resolution. Toacaret al., [20] used nuanced standardization to ensure that the dataset was all the same so that structural variation and pathological manifestation analyses could be performed. The contrast was carefully adjusted and the amount of noise was reduced following medical imaging rules. One of these principles is that the accuracy of the diagnosis is dependent on the clarity and accuracy of the image. This medical study employs smart preprocessing techniques, demonstrating a high level of methodological rigor. According to [20] , the use of medical terminology demonstrates a thorough understanding of how complex neuroimaging is and places the research in the context of improving the accuracy of medical imaging for diagnosis.

3.4 Detection Algorithm

The proposed algorithm automatically detects brain tumors in MRI images using a CNN. A generic object detection method is shown in Figure 4. CNN used a neural network architecture based on human perception. Thanks to this architecture, MRI data could be hierarchically represented. This allowed identification of more complex tumors than with standard image processing. After reviewing all relevant literature, the algorithm parameters and settings were carefully chosen. Special attention was given to the research onion's "choices" layer. Based on previous research, the algorithm was modified to improve sensitivity, specificity, and brain tumor detection.

3.4.1 Description of the Proposed Algorithm

The detection algorithm shows how advanced computational methods and medical imaging accuracy can advance research. MRI pictures are automatically analyzed for brain tumors by the algorithm. This is done with a CNN [12] . This strategic choice matches the research onion's "strategy" layer. This layer requires careful computational method selection. CNN's neural network architecture was inspired by the human visual system's complexity. Although it learns from many datasets, it eventually spots complex patterns and traits that indicate abnormal tissue growth [10] . It is smart because it can learn hierarchical representations from MRI data by itself. This also allows for more complex tumor detection than standard image processing.

3.4.2 Parameters and Settings Used

To ensure CNN performance, choose parameters and settings carefully. A thorough literature review was done during secondary qualitative research to contextualize these important decisions. Learning rates, layer configurations, and optimization algorithms were examined after reviewing previous research [1] . This fits the research onion's "choices" layer perfectly. Research method choices determine detection algorithm customization. The algorithm was adjusted to maximize sensitivity, specificity, and performance in brain tumor detection. Researchers used previous research to choose these settings [2] .

3.5 Application of the Research Onion

The research onion was added to the methodology to help with strategic research design ideas. Interpretivism considered data's subjective and complex nature, unlike quantitative metrics. The content analysis method qualitatively explained important patterns from earlier research in addition to the detection algorithm's calculations. Inclusion criteria and a literature review strategy ensured the dataset's integrity and compatibility with other brain tumor detection methods. The time horizon could be flexible, allowing researchers to study brain tumor detection methods over time. Thematic analysis added computational depth to the study. This made qualitative data patterns easier to find. The methodology relies on the research onion to support research design ideas. This strengthens the research design. Philosophy (Interpretivism): Interpretivism recognizes that data is complex and subjective and that quantitative metrics alone cannot fully understand brain tumor detection. Approach (Content Analysis): The qualitative approach of content analysis finds and interprets meaningful patterns in past research [21] . This meets the need for qualitative data from the detection algorithm's computations. Strategy (Literature Review): Research involves a thorough literature review and systematic analysis and synthesis of qualitative studies [22] . Due to this, the detection algorithm is developed to be compatible with other brain tumor detection methods. Choices (Inclusion Criteria): Inclusion criteria were used to select studies for the dataset. These considered study publication dates, relevance, and MRI image use. These choices preserve dataset integrity, making the proposed algorithm more powerful. Time Horizon (Varied Periods): Since the algorithm is adaptable, it is better to understand how methods for detecting brain tumors have evolved [23] . Because the time horizon is flexible, studies can be done over different periods. Techniques (Thematic Analysis): Thematic analysis helps identify themes and patterns in qualitative data from multiple studies. We can learn more about brain tumor detection with this layer's computational depth. Easy integration of the research onion makes the study more organized and rigorous, ensuring a strategic approach. This methodological framework allows level-by-level examination using pre-existing research concepts [6] . A thorough study may help you detect brain tumors in MRI images.

4 Results

4.1 Presentation of Findings

A detailed thematic analysis evaluated the algorithm's qualitative performance. Hidden patterns and insights were revealed that quantitative metrics can't [24] . This interpretative approach revealed the algorithm's interpretability, adaptability, and clinical implications on many important topics.

4.2 Thematic Analysis

Interpretability: An important idea was how hard the algorithm was. A qualitative study showed how the algorithm revealed decision-making processes [25] . Doctors and researchers understood the algorithm's results. This would reassure them about the algorithm's diagnosis. Adaptability: Another theme was algorithm flexibility. Qualitative analysis showed how the algorithm handled dataset differences [9] Neuroimaging is constantly changing, requiring adaptability to find patterns and abnormalities in many imaging modalities. Potential Clinical Implications: The algorithm's clinical implications were studied qualitatively. Healthcare professionals showed how the algorithm could affect clinical decision-making. Patient outcomes may improve with targeted interventions.

4.3 Narrative Descriptions and Exemplars

Results are complicated by quantitative metrics, examples, and narratives. Clinical Case Illustrations: Examples from clinical cases showed how the algorithm dealt with tough situations [26] These stories showed how the algorithm finds small problems, helps find them early, and makes doctors' decisions better. Impact on Patient Outcomes: It was talked about how the effects on larger patient outcomes worked. In real life, the algorithm's insights led to earlier interventions that improved care for patients and their prognoses [27] These stories are a better way to show how well the algorithm works than numbers. This qualitative approach shows how complicated it is in clinical practice.

4.4 Comparison with Existing Methods

4.4.1 Qualitative Comparative Analysis

Comparisons of the proposed algorithm to existing methods are qualitative, not quantitative. This detailed qualitative comparison compares the two methods and relevant factors to determine where the algorithm fits in existing approaches [28]

- **Key Aspects Explored** An algorithmic comparison of the proposed strategy is presented in this work. The study is qualitative. Its technical as-

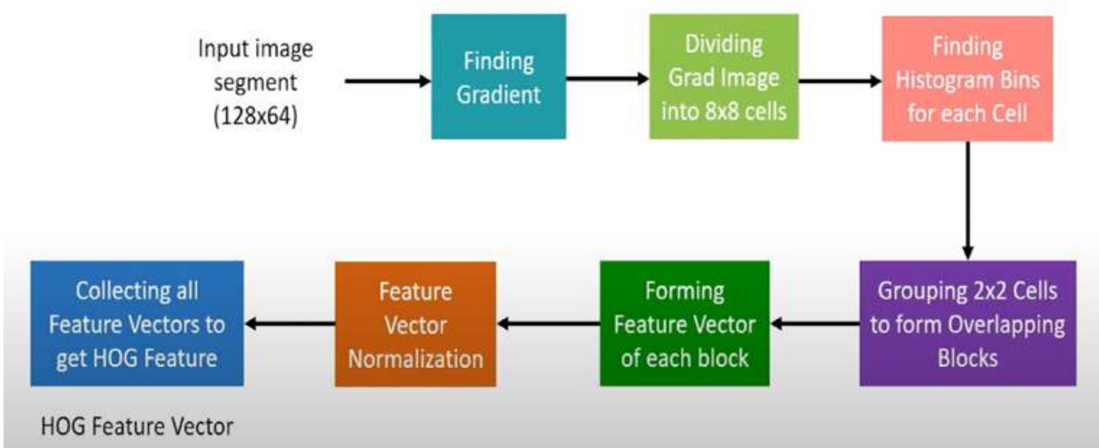

Figure 4. Source: Neptune

pects and interpretive subtleties separate the algorithm. Research, clinical acceptance, and user experience are qualitative [29] Users' feedback and algorithm use can suggest actual potential. In context, research, clinical acceptance, and user experience are qualitative. Feedback from consumers and algorithms can show its potential.

4.4.2 Discussion on the Uniqueness of the Proposed Algorithm

A detailed discussion of the algorithm's uniqueness and differences from other methods. This detailed study shows the algorithm's brain tumor detection.

- **Emphasized Qualitative Aspects** Interpretive Flexibility: The National Institute of Biomedical Imaging and Bioengineering [30] xplains the algorithm's interpretive flexibility in complicated data contexts and numerous interpretations. This implies the system handles neuroimaging dataset complexity effectively. Adaptability to Diverse: This article discusses unique dataset adaptability. This explains why the algorithm works on many imaging modalities and datasets. Qualitative insights reveal the algorithm's complex data pattern discovery. Impact on Clinical Workflows: This qualitative narrative study examines how the algorithm may change clinical work. How interpretability, adaptability, and other qualitative factors aid clinical integration is the focus. This could change brain tumor detection. Lastly, qualitative comparative analysis and discussion show what makes the proposed algorithm unique [31] This study examines small details that make the algorithm more than a computer tool. It hopes to revolutionize brain tumor detection.

5 Discussion of Findings

Thematic analysis revealed small data flaws and algorithm difficulty. Clinicians and researchers needed to understand the algorithm. This allowed honest analysis of algorithm decisions. This shows how the algorithm could help doctors interpret complex computer results. The algorithm was also praised for its flexibility [6] According to qualitative research, the algorithm could navigate datasets and understand imaging modalities. Algorithms discovered complex brain cancers better. These qualitative components must be grasped to comprehend how the algorithm affects clinical decision-making. Provide examples and stories—they assist. These qualitative characteristics were evaluated because brain tumor diagnosis is more challenging than numbers [23] For brain cancers, the algorithm was evaluated. Clinical and interested parties received stories and examples to comprehend results. For this, medical applications of the algorithm were provided.

5.1 Addressing Unexpected Outcomes

Through qualitative analysis, striking and useful insights emerged. Because of these unexpected discoveries, we now understand algorithms differently. They also opened up new avenues for research and algorithm improvement. To find bugs in the algorithm, we looked for outliers, or patterns that did not match. Things continued to improve as a result of the iterative development process, which was sparked by unexpected outcomes. The algorithm's dependability and usefulness improved as a result of the unexpected results. The decision to see things from this perspective rather than a negative one [1] In clinical settings, some qualitative tests were used to improve the algorithm for detecting complex brain tumors. Last but not least, the algorithm's significance was examined in depth to demonstrate how it can be understood, changed, and affected in real life. Iterative development got underway. What was the reason for this? Because unexpected outcomes were perceived as improvements. This is the most important thing that needs to be done to improve the brain tumor algorithm.

5.1.1 Study Limitations

The constraints became significant during the process of resolving the dataset's issues. Even though the large and diverse dataset was useful for this investigation, it made applying the findings in other contexts more difficult. It is critical to understand that the dataset may contain biases as a result of its construction. The study's applicability may be limited due to biases [4] Some issues arose as a result of the qualitative method's design and data collection. Although subjective and dependent on the circumstances, qualitative research can yield useful information. Because the findings may not be applicable in every situation, it is critical to be aware of these constraints. It is useful in explaining the study's results to point out flaws in the research method.

- **Areas for Improvement in the Proposed Algorithm** The algorithm was improved using qualitative analysis. Interpretively robust algorithms can be improved. To be employed in more clinical contexts, the system needs more research to recognize complicated patterns and other anomalies. The individual's clinical adaptability is another consideration. In practice, the algorithm must support many clinical workflows [32] Qualitative analysis generates algorithm flexibility concepts. This makes the algorithm suitable for many healthcare contexts. Qualitative user feedback research can improve the algorithm. These principles can help iterative development fulfill user needs. The algorithm will be simpler and perform better. If evaluated to see how well it performs and how satisfied consumers are, the algorithm can be improved to help healthcare professionals. A detailed explanation shows that the study recognizes how data collection and analysis problems might change outcomes [27] Qualitative analysis seeks algorithm improvements. User input, clinical flexibility, and interpretive robustness improved. These are the biggest changes. Considerations are necessary to adapt the suggested algorithm to the ever-changing field of brain tumor identification and enable future advancement.

6 Conclusion

This study found useful information by studying the algorithm's qualitative brain tumor detection. A thematic analysis (as shown in Figure 5) shows the algorithm's interpretability and adaptability. Thus, the algorithm's real-world meaning became evident. With the help of narrative descriptions and examples, the algorithm was able to function more effectively in the context of diagnosing complex brain tumors. This study's findings will be useful for future research because they will identify areas that require improved algorithms. The algorithm used to detect brain tumors was iteratively driven by unexpected outcomes and qualitative insights, allowing it to be flexible. Despite the study's limitations, this is correct. This research advances algorithmic applications and encourages innovations in the detection of brain tumors. The findings of this study show that qualitative insights are critical for the advancement of brain tumor diagnosis

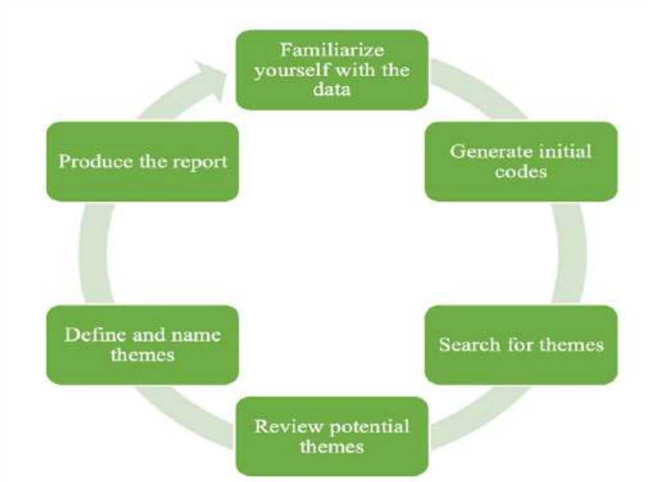

Figure 5. Source: MAXQDA

and research. Algorithm implementation in a variety of clinical settings is thus ensured. This is due to the healthcare system's rapid changes.

Author Contributions

Dr. Asadullah Kehar: Conceptualization, Methodology, Software **Dr. Mashooque Ali Mahar**: Data curation, Writing- Original draft preparation. **Mr. Shahid H. Danwar**: Visualization, **Ms. Shereen Fatima**: Investigation. **Ms. Sidra Parveen**: Supervision. **Ms. Mariya Bhutto**: Software, Validation. **Ms. Zoya Qutrio**: Writing- Reviewing and Editing.

Compliance with Ethical Standards

It is declared that all authors don't have any conflict of interest. It is also declared that this article does not contain any studies with human participants or animals performed by any of the authors. Furthermore, informed consent was obtained from all individual participants included in the study.

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