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Advances in Automated Size Estimation and Geometric Feature Computation in Medical Imaging Using Machine Learning: A Comprehensive Survey

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ABSTRACT: Recently, the integration of machine learning (ML) and deep learning (DL) with medical imaging has improved the accuracy, efficiency and automation of disease detection and diagnosis. Recent investigations have shown that hybrid models, ensemble learning, and multi-modal data fusion are effective diagnostic for vast range of diagnosis and disorder detection. The traditional ML and deep learning model comprises of feature selection, hyperparameter optimization, and automated machine learning (AutoML), exhibiting significant and reliable outcomes. The advancement with transformer-based models, explainable AI, and automated end-to-end exhibits promising clinical translation and personalized healthcare. Despite those developments, lack of standardization of metrics of evaluation, cross-domain generalization, and the implementation of AI solutions into clinical practice. This review paper provides a comprehensive analysis of the existing approaches for future development of research, and highlights the opportunities of AI-based automation to revolutionize medical imaging. Additionally, this paper aimed to improve its precision, accuracy, and detection, as well as classification and quantification of different diseases. The reviewed methodically analyzes the state-of-the-art methods, based on geometric feature extraction, radiomics, size computation with AutoML, and anomaly detection in medical images. The analysis is based on the hybrid model, ensemble learning, and multi-modal data fusion in improving the diagnostic accuracy with particular focus on disorder analysis. Comparative research identifies the advantages limitations of various methods, and the new trends of explainable AI, transformer-based models, and automated model indicate the opportunities of clinical translation. The present paper presented detailed discussion of modern methods, emphasizing geometry feature calculation, radiomics, automated size determination, and anomaly detection in various imaging modalities, such as MRI, CT, ultrasound, and histopathological imaging.

Keywords: Machine learning, deep learning, medical imaging, automated size estimation, geometric feature computation, radiomics, anomaly detection.

Contents

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1. Introduction

In recent years, clinical neuroscience and medical radiology is such brain abnormalities as tumors, lesions, cysts, and structural abnormalities. These anomalies should be identified early enough and rightly quantified to be adequately diagnosed, planned to treat, and a prognosis assessed. Neuroimaging modalities, i.e., magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET) are considered the cornerstone techniques of capturing the brain structures and abnormalities.

The analysis is based on the time consuming, subjective and most likely inter-observer inconsistent because the detached forms of these scans are at the risk of being interpreted by the radiologist [1,2]. The development of computerized computational structures of a reliable detector of anomaly and accurate calculation of size. One of the significant variables of the automated anomaly evaluation and morphological characteristics such as shape, area, volume, surface curvature and texture of an object, are quantitatively expressed in the information about the geometric feature computation [3].

The disproportion of the edges of the tumors, the asymmetry of the brain parts, and the size of the aberrant tissue are crucial indications of the pathological changes [4].

The original models of computation focused on the handcrafted geometric and statistical properties of imaging data. Even though these techniques were effective in the derivation of principal features, was likely to produce noise and low differences as well as variability in patients [5]. With the growing complexity of neuroimaging data, there has been a paradigm shift towards the more widespread use of the recent developments in machine learning (ML) and deep learning (DL) to extract features, identify anomaly, and perform volumetric analysis of the data [6]. The classical ML algorithms such as support vector machine (SVM), the random forests and k-nearest neighbors (KNN) were broadly applied in the categorization of anomalies based on the geometric features [7]. These models proved to be more accurate than the conventional statistical methods, through feature engineering, limiting their extrapolation capability to non-homogeneous data sets [8].

Deep learning revolutionized the sector since it enabled automatic extraction of features of imaging information. The use of convolutional neural networks (CNNs) and its derivatives (U-Net, V-Net, 3D CNNs) has shown state-of-the-art performance in brain tumor segmentation, lesion detection, and volumetric computation [9,10]. In comparison to the classical ML approaches, the DL models are provided with training to learn a hierarchical representation of both geometric and contextual features to enhance the accuracy of the anomaly detection procedure and minimise human intervention [11]. The correct calculation of the size of the brain anomalies is one of the most crucial clinical requirements since the volume of the tumor and the size of the lesions directly influence the selection of treatment options, their surgical planning, and monitoring of the disease [12]. To use the examples, concerning the treatment of glioblastoma, any minor error in the contours of the tumor may radically alter the outcomes of the treatment [13]. Radiologists determine the size by hand which is very cumbersome and may lead to enormous error in intra and inter observer [14].

The accuracy and scalability of automated size computation models have also been greatly enhanced using models that use both a geometric feature extractor and ML/DL-based segmentation [15]. Besides, sophisticated algorithms also give the possibility of longitudinal tracking so that clinicians can trace the rates of anomaly development, and, in addition, measure the effectiveness of treatment [16]. The advancement of conventional techniques exhibits the significant limitations associated with the conventional techniques.

Geometry characteristics are highly delicate in the imaging calculation, noise, and patient variability calculation [17]. Through training of DL models requires large annotated datasets that are not easily available in the medical profession since they are expensive and immoral to annotate [18]. Besides that, black-box of DL methods would also contribute to the interpretability issue, which restricts their applicability in clinical practice [19].

Hybrid models with trained features of ML/DL structures that mix handcrafted geometric features with them are becoming popular in order to address them.

These models unite the representativeness of the geometrical component and the discriminative power of the DL representations, and introduce a harmonious architecture of the solid anomaly detection [20]. The other dimension is the integration of the multimodal imaging data in which the properties of the MRI, CT and PET are applied to make the diagnosis more accurate. It is proved that multimodal fusion can share the information in such a way that a complementary information is received, and it is easier to detect and estimate the size of anomalies [21]. In addition, neuroimaging brain aberration detection systems with explainable visualizations on which clinicians can use are also being developed using explainable AI (XAI) techniques [22]. These innovations are gradually bridging the computational intelligence-clinical trust challenge.

Testing and reporting standards on neural tissue models. These reference standards such as BraTS (Brain Tumor Segmentation Challenge), ADNI (Alzheimer's Disease Neuroimaging Initiative), OASIS and TCIA provide standardised platforms to develop and evaluate neural tissue models [23]. In a similar environment, such datasets can be employed to perform a comparative analysis of various algorithms that can facilitate reproducibility and extrapolation. However, the problems of heterogeneity of datasets, biases in annotations, and the lack of rare examples of anomalies also remain significant bottlenecks [24]. Thus, to alleviate the issue of data shortage and privacy in neuroimaging tasks, self-supervised learning, transfer learning, and federated learning are currently under investigation [25]. The clinical significance of automated computation of geometric features combined with ML/DL is significant. These models can revolutionize neuro-oncology, neurodegenerative disease treatment, and neurosurgical planning, as they can help radiologists to make a diagnosis faster and provide real-time monitoring of treatment [26].

The use of automated systems in detection of anomaly in the brain will further increase as the computational power, availability of data, and algorithmic complexity continue to advance. Future opportunities involve the addition of multimodal fusion, XAI-based interpretability, and integration with personalized medicine models to make clinical adoption comprehensive [27]. Eventually, the developments should make available a robust, scalable and clinically interpretable solution to early diagnosis and proper calculation of magnitude of brain anomalies [28]. It is a systematic literature review of the state-of-the-art in automated geometric feature computation and state-of-the-art ML/DL in brain anomaly detection and size computation.

This paper begins by discussing the potential imaging modality that may be utilized in the detection of anomalies, and then geometric features that are commonly generated by neuroimaging data are defined. We then discuss classical ML and modern DL models, which are used in automated detection, with the specific focus of their ability to calculate the size of anomalies properly. The existing practices are compared and the strengths and weaknesses of the practices are identified. Finally, we make remarks on the clinical use, barriers, and future opportunities, and we give an observation on how such technologies can be successfully integrated into the healthcare systems to improve patient outcomes.

2. Brain Imaging Modalities

Neuroimaging forms a basis for the detection mechanism for classification as well as monitoring of abnormalities in the brain. Structural, functional, and metabolic information about the physiology of the brain is available using modalities like magnetic resonance imaging (MRI), computed tomography (CT), positron emission tomography (PET), functional MRI (fMRI), diffusion tensor imaging (DTI), and ultrasound. Recent developments showed that multimodal imaging employed together with machine learning (ML) and deep learning (DL) can contribute to a massive enhancement of the accuracy of any anomaly detection and size calculation [16]. This section is a review of the existing methods in the estimation of different modalities those are integrated with ML/DL methods and how they can be applied to the automated computation of geometric features in brain anomaly detection. Figure 1 illustrated the process in the medical image processing which illustrates the major medical imaging modalities used for brain analysis, including MRI, CT, fMRI, resting-state fMRI (rs-fMRI), diffusion tensor imaging (DTI), positron emission tomography (PET), and emerging computational approaches. The diagram highlights how structural, functional, and physiological imaging methods contribute to comprehensive brain assessment.

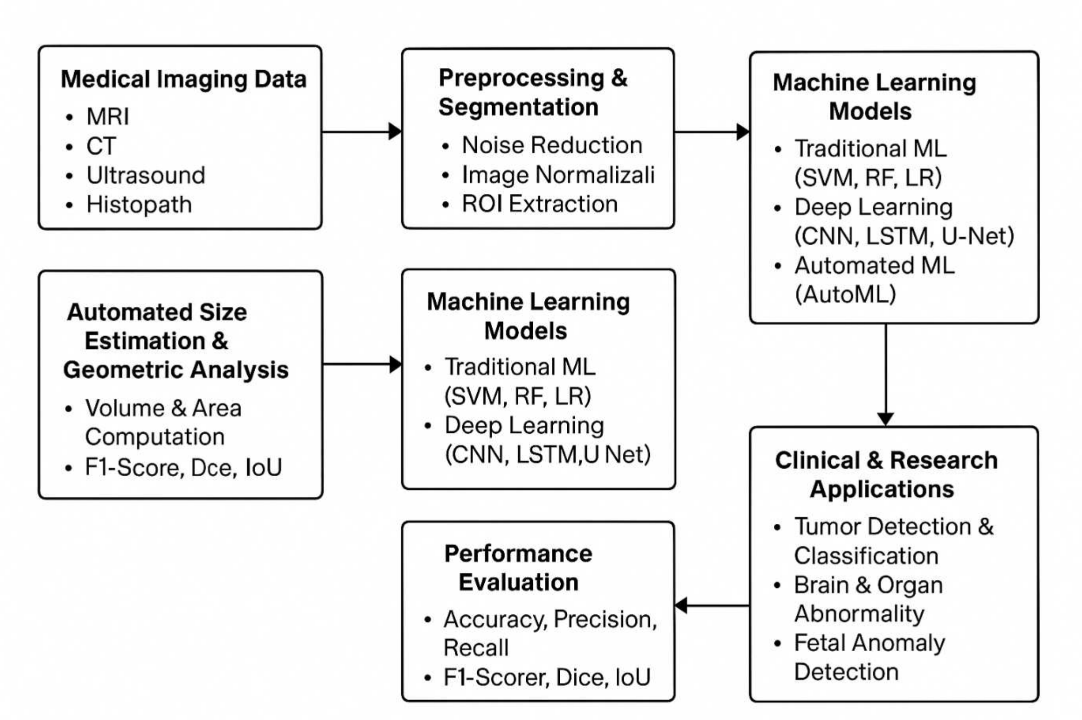

Figure 1: Modalities in Brain Imaging

2.1. Magnetic Resonance Imaging

MRI is the traditional standard for non-invasive imaging of the brain because of its excellent ability to obtain a high spatial resolution and the possibility of obtaining soft tissue contrast. The traditional MRI methods including T1-weighted, T2-weighted and FLAIR sequences cannot be neglected in visualization of tumors, lesions and neurodegenerative alterations. In addition to conventional imaging, multimodal MRI (structural, functional, and diffusion imaging) has also been utilized more often and more extensively to investigate neurocognitive functioning [16]. Tay et al. [16] showed the application of multimodal MRI and ML models to assess neurocognitive capacity in patients with systemic lupus erythematosus, which has proven the modality to be versatile outside of the classical neurological conditions. The development of MRI-based anomaly detection has also concentrated on fetal and pediatric application. Research indicates the combination of ML algorithms with fetal brain scans to predict early onset developmental abnormalities [17,22,23,32]. This type of innovation is especially essential, as the structural anomalies in the fetal brain are sometimes difficult to notice by hand, and the opportunities to do it earlier is therefore missed. The children's MRI-based technique uses ML models for rare disorders, including Duchenne muscular dystrophy, which have demonstrated particular brain changes in association with neurocognitive conditions [21]. The figure 2 presented the medical imaging process in the neuroscience. The overall summary of the presented literature are presented in Table 1.

2.2. Computed Tomography

Computed Tomography (CT) imaging continues to play a critical role in neuroimaging, particularly in time-sensitive clinical scenarios. One of its most prominent applications is in the management of traumatic brain injury (TBI), where rapid acquisition and immediate availability make it indispensable. In acute care, clinicians often require fast and accurate diagnostic imaging to make decisions that directly affect survival and long-term outcomes. These advantages are achieved by CT as it offers fast and dependable visualization of internal brain structures with the ability to detect life-threatening abnormalities such as intracranial hemorrhages, hematomas, contusions, skull fractures, and cerebral edema. Despite the overwhelming recognition of Magnetic Resonance Imaging (MRI) as the gold standard of both structural and functional imaging with a high level of resolution, CT imaging is still the best in an emergency due to the speed and availability of the method as well as its sensitivity to acute pathological changes. Machine learning (ML) methods have gained use in CT neuroimaging, especially in the detection of anomalies in TBI, in recent years. ML algorithms are especially effective at detecting hidden trends in imaging data that traditional radiological measurements might fail to conform to, demanding specific resources that may be scarce in resource-constrained settings where radiologists may be somewhat scarce. As an example, Pierre et al. [28] performed a review of the role of ML in TBI imaging and only stated that, although the progress is promising, there are still a number of gaps to address. The lesion detection workflows of CT imaging are at infancy, and issues of standardization, generalization of models across institutions and their integration into clinical workflows have hampered its usage. These drawbacks highlight the need to create more significant and interpretable ML-based models capable of supplementing clinician experience instead of substituting it. Among the most important benefits of CT imaging as an anomaly detection method, one can include the capacity to record the complementary geometric information.

CT scans are also found to be especially useful in identifying calcifications and bone abnormalities, which are relevant in acute and chronic neurological conditions unlike MRI. Geometric characteristics obtained using CT images which include size, volume, and shape of lesions or fractures are useful quantitative characteristics that are not fully exploited in traditional methods of diagnosis. These geometric properties can be integrated into ML models to enhance the accuracy of anomaly detection in addition to clinical interpretability of the results. Indicatively, volumetric computation of hematomas or contusions give important information on the severity of brain injury, which consequently makes a difference in prognosis and treatment outcomes. What is more, CT images may be successfully combined with MRI to obtain a more comprehensive diagnostics image. Although MRI outdoes CT in soft tissue contrast and the definition of microstructural pathology, CT provides complete complement to it by bringing out clearly boundaries of hemorrhages, calcifications, and fractures. This multimodal methodology can greatly improve the task of detecting the anomalies and volumetric analysis. In this regard, researchers and clinicians can use a combination of CT, where geometric precision is necessary, and MRI, where structural understanding is required to compute the spatial extent and progression of lesions more precisely. Such a combination is especially helpful in creating sophisticated ML-based pipelines, which attempt to combine anomaly detection with quantitative feature extraction.

2.3. Functional MRI (fMRI) and Resting-State fMRI (rs-fMRI)

Functional Magnetic Resonance Imaging (fMRI) has become one of the most potent instruments of contemporary neuroimaging, which has provided an insight into the dynamic activity of the brain. As compared to structural MRI which mainly emphasises the anatomical characteristics of the brain, fMRI is functional in nature, as it detects blood-oxygen level dependent (BOLD) signals. These are the localized variations of blood flow and oxygenation which are triggered by neural activity, and through which the researchers and clinicians can deduce patterns of brain activity. This non-invasive mapping of the brain function has allowed fMRI to become indispensable both in research and clinical settings. One of the most significant developments in the field of fMRI is resting-state fMRI (rs-fMRI), performance of which records the activity of the brain when a person is not performing a particular cognitive task. Through analysis of the intrinsic variability of the BOLD signal, rs-fMRI can be used to study functional connectivity of large-scale brain networks. This technique has been particularly helpful in the study of psychiatric and neurodegenerative diseases, in which the dysfunction of ill-defined functional structures can arise without apparent structural abnormalities. As opposed to task-based paradigms, which entail patient obedience, rs-fMRI is less impractical and may be employed in a broader group of populations, including children, older patients, and persons with cognitive deficits.

FMRI and rs-fMRI have wide clinical and research applications. Functional imaging has delivered new information in the field of psychiatry not only of major depressive disorder (MDD), but also of schizophrenia and anxiety disorders, where the conventional structural scans frequently do not show abnormalities. An example is a study by Luo et al. [31] who suggested an interpretable machine learning (ML) method based on multi-feature concatenation and stacking of classifiers on the data of the rs-fMRI to differentiate MDD. Their findings showed the possibility of ML-driven fMRI analysis to detect subtle and distributed functional changes in psychiatric patients, and more objective diagnostic instruments in mental health became possible. Notably, one of the main issues with the application of ML to clinical practice considered by the interpretability of their approach was to make sure that its models provide not merely accurate but also comprehensible results that clinicians can rely on. Equally, Zhong et al. [18] made use of multimodal ML analyses to identify disturbed large-scale brain networks in patients with glaucoma in the field of neuro-ophthalmology. Their paper has pointed out the role of rs-fMRI in revealing reorganization in functional aspects that is not evident in structural imaging and in increasing the diagnostic capabilities of neuroimaging beyond the traditional anatomical features. This observation highlights the applicability of fMRI as a modality that is able to record both direct disease effects as well as compensatory neural adaptations in a wide range of conditions. In addition to single disorder studies, fMRI has also played a role in the generalization of the orchestration of the brain networks. Some of the important functional networks that were mapped and extensively explored using the rs-fMRI are the default mode network (DMN), central executive network, and salience network. Malfunctions in the interrelationship of these networks have been considered to be behind a broad range of neurological and psychiatric disorders, including Alzheimer disturbance as well as attention-deficit hyperactivity disorder (ADHD). These insights have been further enhanced by the capability of ML algorithms to process high-dimensional data in the form of rs-fMRI data, which allows further classification of patients and could be used to predict the development of the disease.

2.4. Diffusion Tensor Imaging (DTI) and Structural Connectomics

Diffusion Tensor Imaging (DTI) is an effective MRI modality that has the capability of quantitatively describing the movement of water molecules in brain tissue. In contrast to standard MRI, which focuses on macroscopic structural information, the DTI offers microstructural data by tracing the directional flow of water along white matter tracts. Being anisotropic, that is, water diffusing easier in the brain along axonal fibres than across them, DTI is able to both measure the integrity of the white matter pathways as well as their orientation. This allows it to be of special use in studying connectivity, mapping neural circuits, and detecting subtle abnormalities that cannot be seen in structural scans. Anomaly detection is one of the most important DTI applications. Since most neurological disorders disrupt the microstructure of the white matter, DTI has the ability to display the sign of pathology at an early stage. As an example, in oncology, DTI can be used to determine tumor infiltration regions. Traditional MRI may outline the apparent tumor bulk, however, DTI has the capability to detect areas of impaired diffusion pattern surrounding the tumor that signify microscopic tissue infiltration. This is the finer detail that gives neurosurgeons the necessary information about the surgical planning so that they can minimize harming functional white matter tracks in the process of tumor excision. Equally, DTI is commonly utilized in research of neurodegenerative pathologies, in which the progressive impairment of the integrity of white matter is a typical phenomenon. DTI allows tracking disease progression and response to treatment by measuring the change in diffusion parameters like a fractional anisotropy (FA) and mean diffusivity (MD).

Machine learning (ML) has only increased clinical utility of DTI by making it possible to analyze its high-dimensional datasets in a more sophisticated way. It has been shown that ML-based techniques can uncover patterns in DTI measures that could not be found using conventional statistical methods. An example that can be used is that studies have indicated that using ML models with DTI data can effectively detect disrupted connectomes in pathologies like vestibular migraine [25]. DTI-derived features in these situations give biomarkers of abnormal connectivity, and the magnitude of network dysfunction can be caused by the smallest changes in microstructural integrity. These results can facilitate both early diagnosis and provide information on the pathophysiology of these complicated neurological conditions. Another advantage of DTI is that it is compatible with multimodal imaging methods. In combination with structural MRI, functional MRI (fMRI), or even PET, DTI supplements the receptor set with geometric and microstructural data to anatomical and functional data. Such a combination gives a more detailed picture of brain anomalies. As an illustration, the use of DTI together with MRI improves the quality of computation of the boundaries of abnormalities through the merging of microstructural integrity maps and high-resolution structural detail [24 and 25]. These multimodal approaches have been especially useful in enhancing volumetric estimates of tumors and lesions, which eventually can lead to a better planning of the treatment, and prediction of the outcome.

2.5. Positron Emission Tomography (PET) and Multimodal Integration

Positron Emission Tomography (PET) is a functional imaging modality that captures the metabolic activity of tissues by tracking the distribution of radiotracers, most commonly Î8F-fluorodeoxyglucose (FDG). Unlike structural imaging methods such as MRI or CT, which provide high-resolution anatomical information, PET focuses on the biochemical and physiological processes underlying tissue function. Because many pathological processes, particularly in oncology, involve altered metabolism, PET imaging serves as a highly sensitive tool for detecting anomalies that may not be apparent on structural scans. For example, malignant tumors often demonstrate elevated glucose uptake due to accelerated cell proliferation, allowing PET to identify active tumor regions with remarkable accuracy. The clinical value of PET is particularly evident when it is integrated with anatomical imaging modalities such as MRI or CT. PET-CT Hybrid systems have long been the rules in oncology, where structural and metabolic data are integrated together with the aim of enhancing the diagnosis and staging. Of more recent interest are hybrid PET-MRI models, which provide the concomitant acquisition of structural, metabolic and even functional information with the same scan. This multimodal combination fills the biology-metabolism gap, allowing lesions to be co-localised accurately and a broader feature space both to make clinical decisions and to be analysed by computation.

PET complementary to MRI is of particular importance in anomaly detection and disease monitoring. Although MRI is the most accurate in defining structural abnormalities, PET provides information about areas of abnormal metabolic activity which is frequently the antecedent of apparent anatomical alteration. This renders PET essential in the segmentation of tumors, monitoring their progression as well as tracking of treatment [26]. An example is in glioblastoma where MRI can be used to identify the size of the visible tumor mass, whereas PET can tell the difference between active tumor tissue, peritumoral edema and necrotic tissue. The differentiation is essential to proper boundary calculation as false treatment by taking necrosis or edema as tumor tissue can be overestimated and lead to inefficient treatment plans. Machine learning (ML) frameworks have further enhanced the diagnostic and prognostic potential of PET, particularly when used in conjunction with other modalities. Falcó-Roget et al. [26] demonstrated a ML-driven approach that integrates PET with functional MRI (fMRI) to study tumor-driven reorganization of brain function. Their work revealed dynamic interactions between structural and functional networks during disease progression, highlighting how tumors not only alter local metabolism but also disrupt broader brain connectivity. This type of multimodal ML analysis opens new avenues for understanding the systemic impact of tumors and tailoring personalized interventions.

2.6. Ultrasound Imaging

Ultrasound provides a cost-effective, real-time imaging modality, especially relevant for fetal brain anomaly detection. Unlike MRI or CT, ultrasound is non-invasive, portable, and safe for repeated prenatal screenings. ML/DL approaches have significantly advanced its utility. Olsen et al. [22] applied unsupervised denoising diffusion models for fetal brain anomaly detection, while Shamya et al. [23] presented a comparative analysis of DL-based approaches for ultrasound-based anomaly detection. Subburaj and Pandiyarajan [32] also proposed DL frameworks for fetal brain prediction, showing that deep models outperform conventional techniques in terms of accuracy and generalizability.

The figure 2 presents a hierarchical organization of brain imaging techniques, showing the relationships among structural imaging (MRI, CT), functional imaging (fMRI, rs-fMRI), diffusion-based imaging

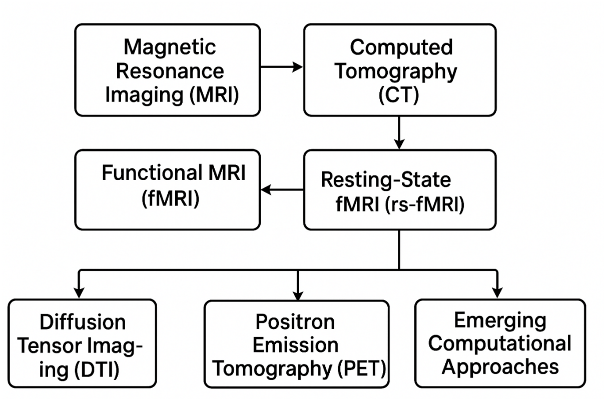

Figure 2: Classification of Imaging Techniques

(DTI), metabolic imaging (PET), and evolving computational imaging approaches. The structure demonstrates how different modalities complement each other in brain anomaly detection.

Table 1: Summary of Modalities

Modality	Advantages	ML/DL Integration	Application	References
MRI (Magnetic Resonance Imaging)	Gold standard for high-resolution structural & soft tissue contrast; multimodal variants (T1, T2, FLAIR, DTI, fMRI)	ML models applied to multimodal MRI (structural, functional, diffusion) for neurocognitive and pathological assessments	Tumor/lesion visualization, fetal & pediatric anomaly detection, volumetric measurement of neurodegenerative alterations	Tay et al. [16], Peruzzo et al. [21], Jiang et al. [1]
CT (Computed Tomography)	Fast, accessible, excellent for emergencies (TBI, hemorrhage, skull fractures); good for calcifications & bone	ML used for automated lesion detection in TBI, but workflows still developing	Size/volume computation of hematomas, contusions; complementary with MRI for boundary detection	Pierre et al. [27,28], Ahmed et al. [13]
fMRI & rs-fMRI	Captures dynamic brain activity via BOLD signals; rs-fMRI useful for functional connectivity	ML improves classification of psychiatric/neurodegenerative disorders, interpretable models for clinical trust	Functional connectivity mapping, anomaly detection in MDD, schizophrenia, glaucoma, network-based volumetric analysis	Luo et al. [31], Zhong et al. [18], Taspinar & Ozkurt [10]
DTI (Diffusion Tensor Imaging)	Tracks white matter microstructural integrity, connectivity mapping	ML extracts hidden biomarkers of disrupted connectomes; supports multimodal integration	Tumor infiltration mapping, microstructural integrity loss detection, refined volumetric tumor/lesion boundary computation	Chen et al. [25], Beizaee et al. [24]
PET (Positron Emission Tomography)	Measures metabolic activity (e.g., FDG uptake); highly sensitive to tumor activity	ML frameworks integrate PET with MRI/fMRI for multimodal analysis of tumor reorganization	Tumor segmentation, progression tracking, distinction of active tumor vs edema/necrosis, automated volumetric computation	Falcó-Roget et al. [26]
Ultrasound	Safe, portable, real-time; highly suitable for fetal brain imaging	DL models for anomaly detection, denoising diffusion models for robust predictions	Early prenatal detection of brain anomalies, prediction of developmental disorders	Olsen et al. [22], Shamya et al. [23], Subburaj & Pandiyarajan [32]

Recent advances have expanded the frontiers of neuroimaging through innovative computational frameworks. Beizaee et al. [24] introduced rectified flow models for efficient anomaly correction, demonstrating improved robustness in correcting structural irregularities in brain scans. Similarly, Sadeghian et al. [33] proposed HyperBrain, an anomaly detection model for temporal hypergraph brain networks, providing novel insights into the temporal progression of anomalies. These approaches signal a shift from static, single-modality imaging toward dynamic, graph-based, and corrected imaging workflows that enhance feature computation for ML-based anomaly detection. Hybrid models are also emerging as powerful tools. Celik and Inik [20] developed optimized hybrid architectures combining DL and traditional ML for multiclass tumor detection, achieving superior accuracy compared to standalone models. Likewise, Appiah et al. [34] integrated proper orthogonal decomposition with deep learning to enhance tumor detection accuracy, while Malakouti et al. [29] and Abdelrahman Ali et al. [30] explored transfer learning and biosensor-assisted approaches for brain tumor classification and early detection, respectively. The clinical translation of brain imaging modalities integrated with ML/DL models is both promising and challenging. Studies consistently highlight improvements in diagnostic accuracy, anomaly detection rates, and volumetric precision [19,20,34]. Yet, concerns remain regarding generalizability, interpretability, and data availability. Kumari et al. [27] comprehensively reviewed ML/DL anomaly detection methods and stressed that despite advancements, reproducibility and clinical trust are ongoing challenges. Data heterogeneity, imaging artifacts, and annotation inconsistencies continue to impede robust deployment in clinical settings [28].

3. Geometric-Based Approaches

Geometric feature computation forms the cornerstone of automated medical imaging analysis, particularly in brain anomaly detection and size computation. Unlike purely pixel-intensity–based methods, geometric features capture the shape, topology, curvature, texture, and spatial relationships of anatomical structures, offering a robust foundation for identifying irregular morphologies associated with tumors, lesions, and other anomalies. These descriptors—ranging from boundary irregularities to volumetric properties—are clinically relevant because many pathologies manifest as geometric distortions in normal anatomy [34,35]. Integrating these features with advanced machine learning (ML) and deep learning (DL) models has substantially improved both anomaly detection and volumetric estimation accuracy. Table 2 presented the image modalities method in the machine learning based deep learning approach, Table 3 presented the geometric feature estimation in the imaging modalities for the image processing.

3.1. Classical Geometric Approaches in Brain Anomaly Detection

Long-standing methods of geometric feature computation of neuroimaging have traditionally focused on hand-to-crafted features based on tumor or lesion morphology. Tumor diameter, surface-to-volume ratio, circularity, compactness, fractal dimension, and edge sharpness were common geometric parameters that were derived using MRI, CT, or other types of neuroimaging in order to provide a quantitative foundation to classification and diagnosis. The usefulness of these descriptors was especially due to the fact that they were interpretable: clinicians could find the relationship of a more irregular shape of the tumor, or a sharp boundary of an edge, intuitively relatable to aggressive pathology. As such, they were used as valuable inputs to early machine learning (ML) classifiers, e.g. support vector machines, k-nearest neighbors, or logistic regression, in classifying normal and abnormal brain tissues. But the use of handcrafted descriptors had a variety of limitations. To begin with, they were very dependent upon the segmentation step which is one of the most difficult areas of analysis of neuroimaging. Tumor boundaries might poorly be segmented and thus error may easily be propagated into geometric measurements, thus reducing the performance of the classifier. Second, these properties were susceptible to imaging noise and acquisition variations, especially in technologies such as MRI and CT where the intensity artifact or motion-induced distortion are prevalent. Third, simple or homogeneous lesions were adequately described using handcrafted descriptors, but a more complex, heterogeneous, or infiltrative lesion was often poorly described by them. As an example, irregularly-growing tumors or overlapping edema often could not be well characterized by simple metrics based on the shape.

In order to overcome these limitations, the discipline has gradually been moving towards a model of hybrid approaches that combine classical geometry and contemporary data-driven approaches. The introduction of dimensionality reduction and orthogonal decomposition methods, where geometric features can be expressed in a smaller and more noise robust form, is one such direction. As an illustration, proper orthogonal decomposition (POD) has been studied to represent major geometric patterns and remove irrelevant or less informative variations. It is expected that by integrating such mathematical formalisms in deep learning (DL) networks, researchers will be able to combine the interpretability of geometric features with the predictive capabilities of the current neural architecture. Appiah et al. [34] made a significant step in that direction and suggested a POD-based framework with deep networks to identify brain tumors. Their work showed how classical geometry could be incorporated into highly ML pipelines with a beneficial impact on resistance to segmentation errors and noise and still with the benefit of maintaining the clinical interpretability of geometric features. Notably, the integration did not only reduce the accuracy of the anomaly localization but also provided the capability of having more reliable volumetric and boundary computations. Such a work is a good example of a developmental tendency in the profession: instead of completely abandoning handcrafted descriptors, researchers are rebranding their own activities in hybrid ML/DL environments.

3.2. Algebraic and Differential Geometry in Imaging

Over the past few years, algebraic topology and differential geometry have become the new frontiers of medical imaging feature computing, especially in neuroimaging imaging tasks where traditional Euclidean descriptors are usually inadequate. Classical shape-based measures like circularity, compactness or surface-to-volume ratios only represent rough geometrical characteristics of the brain abnormalities. Tumors and lesions, however, are frequently of very non-Euclidean morphology, requiring more sophisticated structures to describe their complexity. To solve this, scientists have resorted to topological and manifold-based models that can explain the higher order structural relations in medical pictures. The frameworks presented by Levenson et al. [35] are based on topological invariants and manifold learning and allow modeling brain tumor morphologies in non-Euclidean forms. These methods represent an inherent structure of data in terms of relational properties, e.g., connectivity and continuity, as opposed to depending on mere absolute geometric quantification. Indicatively, manifold-based learning can determine the distribution of tumor tissues on a high dimensional, curved, manifold feature space, without distorting relationships as a simple linear projection technique would. It proves especially useful in the field of neuro-oncology, in which the patterns of tumor invasion of adjacent white matter can be highly non-linear and disordered.

Persistent homology is one of the topological tools that have been studied most and used to represent tumor margin irregularities. Persistent homology operates by examining the topological characteristics of data (e.g. connected components, loops, and voids) using a series of scales, thereby giving a multi-resolution description of the shape and structure of tumors. This can be used in clinical imaging as subtle shape abnormalities (e.g. spiculated tumor edges or irregular contour indentations) can be quantitatively described. Irregular margins are known to be some of the early signs of malignancy and in this regard, persistent homology can give important diagnostic information that cannot be reflected by standard descriptors. Such techniques are also a factor towards computational efficiency. The extraction of features as a topological signature allows the extraction to be more resistant to noise, resolution variations and modality variations (e.g. MRI vs. CT). It implies that topological descriptors will be able to make more generalizations across heterogeneous data to solve one of the perennial problems in medical image analysis. Moreover, since topology is concerned with invariant structural characteristics, it becomes less sensitive to slight differences in the accuracy of segmentation, which is a significant weakness of handcrafted geometric features. Notably, the integration of the best topological and differential geometrical approaches is in tandem with the tenets of precision medicine. The techniques give extremely personalized characterizations of anomalies, in terms of their fine structural and topological properties, which can distinguish subtle patient-specific variations. Two tumours of the same volume can, as an example, have very different signatures in terms of topology, some with smooth borders, and others with strongly irregular and infiltrative features. The implications of such differences can be far reaching as regards to prognosis and treatment planning especially when it comes to planning surgical resection or radiotherapy margins. Outside of anomaly detection, they are also being used in hybrid ML/DL pipelines, where topological features are used to complement deep features of convolutional or transformer-based networks. This hybridization enables models to enjoy the advantages of learning features data-driven and principled structural descriptors mathematically, and thus attaining greater accuracy and interpretability. Consequently, algebraic topology and differential geometry are being considered also as a practical tool in clinical neuroimaging workflows, and are moving the field towards increasingly explainable, robust, and personalized computational models.

3.3. Deep Learning and Automated Feature Extraction

The switch towards the deep learning (DL)-based feature extraction of handcrafted geometric descriptors has facilitated a shift in the paradigm of neuroimaging analysis. Conventional methods used features generated manually such as tumor diameter, compactness or surface irregularities and demanded knowledge of the domain, and were very sensitive to image artifacts and segmentation errors. These techniques offered an interpretability but tended to be weak and generalized poorly when used on a heterogeneous dataset. In comparison, DL-based pipelines can be trained using imaging data to learn hierarchical representations without explicitly designing features, and learn a wide range of local to global geometric patterns. This change has not only promoted accuracy in anomaly detection but as well permitted the derivation of more subtle and clinically relevant geometric cues. The feasibility of such an approach was illustrated by Saboor et al. [38], who came up with a DL-based deep feature classification model to detect brain tumors on MRI scans. Their structure performed better than the traditional geometry-only pipelines and it learned geometric abstractions using the raw images data. Their model represented data-driven replications of tumor boundary irregularities, intra-tumor heterogeneity, and geometric asymmetries without the use of fixed set of predetermined descriptors. This flexibility is especially needed in neuro-oncology because the morphology of many tumors and tumor subtypes differs considerably among patients. In the same manner, Lamba et al. [49] made a step forward in this area as they developed a system of integrated DL-supervised learning that integrates geometric features into MRI series. They did not ignore the geometric cues but instead combined them with deep features, capitalizing on the complementary benefits of both types of representations. The outcome was enhanced sensitivity of early-stage tumor detection, in which geometric deformations can be subtle and difficult to notice by either handcrafted or solely DL-based pipelines alone. This middle ground is a demonstration of the usefulness of a hybrid of geometric interpretability, and the representational ability of DL architectures, especially to clinical adoption, where explainability is still paramount.

One such potentially fruitful area is the application of graph-based architectures to geometric feature learning. Although convolutional neural networks (CNNs) are very useful in local pattern recognition, they might fail to resolve the non-Euclidean associations and higher-order associations among the tumor morphologies and adjacent brain structures. Graph neural networks (GNNs) and modern memory networks like graph transformers offer a versatile approach to modeling spatial and relational relationships by modeling imaging features as nodes and geometric relationships as edges. A hierarchical graph pyramid transformer that was proposed by Liu et al. [42] is used to diagnose cancer in histopathological images. Their research was, however, on pathology slides, but its approach is very applicable to brain imaging. Graph transformers are able to encode geometric dependencies between the regions of interest to capture multi-scale structural features, including the dependence between the margin complexity of a tumor and the infiltration of adjacent tissue. By having this approach translated to neuroimaging it would be possible to have models that reason not only about individual voxels or patches, but about the geometric interactions between anomalies and the surrounding brain anatomy.

Furthermore, the fact that these models are hierarchical is very beneficial to neuroimaging. On lower levels, they are able to pick fine-grained geometric detail, e.g., inaccurate edge irregularities or clusters of micro-lesions. At the higher levels, they are able to generalize them into global structural pattern, like ventricular displacement, or hemispheric asymmetry, which is an important biomarker in such conditions as glioblastoma, hydrocephalus, or traumatic brain injury. Such multi-scale geometric reasoning is quite appropriate to clinical requirements, where local detail and global context are both used to make diagnosis and treatment decisions. The advantage of graph-based and DL-driven geometric modeling is another capability to deal with multi-modal integration. Combining MRI, CT, PET, and diffusion tensor imaging (DTI) enables the relationship between modalities to be encoded naturally, such as between metabolic activity (PET), structural deformation (MRI/CT) and white matter tract disruption (DTI). The fact that such multimodal geometric fusion is a step towards holistic characterization of anomalies, which is no longer limited to the singular modality. Finally, the development of handcrafted descriptors to DL-based and graph-based representations is part of a larger shift towards automated, scaleable and more clinically flexible geometry computational models. Even though handcrafted features provided interpretability, they were not that strong in reality. DL models are more accurate and scalable, whereas graph-based ones present relational reasoning, which is a promising direction in the explanation of, but powerful, geometric feature learning pipelines to detect brain anomalies and compute sizes.

3.4. Hybrid Feature Computation Models

Hybrid models combine handcrafted geometric descriptors with automatically extracted deep learning (DL) features, aiming to balance interpretability and predictive power. To ensure robust evaluation, incorporating standardized metrics such as the Dice Coefficient and Intersection over Union (IoU) is recommended for quantifying segmentation and detection performance. Li et al. [39] demonstrated this by integrating hybrid features with optimized ML hyperparameters for lung cancer detection. In brain imaging, similar frameworks enhance generalizability by leveraging handcrafted shape descriptors alongside DL-derived embeddings. For example, Sharif et al. [46] combined binomial thresholding with multi-feature selection to improve segmentation accuracy, showing that handcrafted geometric descriptors remain valuable when fused with modern feature selection and ML optimization. Likewise, Kalita and Borgohain [44] used ocular geometry-based biomarkers for glaucoma diagnosis, highlighting the broader applicability of geometric computation across neurological imaging domains.

Radiomics, which extracts high-dimensional quantitative features from medical images, represents another critical hybrid application. Radiomics pipelines compute shape, intensity, and texture features for classification or prediction tasks. Alqahtani et al. [43] presented a radiomics-based ML framework for carcinoma grade and stage prediction—serving as a "virtual biopsy" alternative to invasive sampling. Translating such radiomics-based geometric frameworks into brain imaging could enable non-invasive tumor grading and prognosis prediction. Beyond static imaging, geometric feature computation has been extended to temporal and physiological imaging contexts. Zhang et al. [37] proposed a constraint-aware ML framework for fractional flow reserve estimation from coronary imaging, emphasizing dynamic geometry computation in vascular analysis. Zheng et al. [41] extended this idea using recurrent neural networks for intracoronary images. Although these studies focus on cardiology, their principles can be adapted for longitudinal brain imaging, enabling dynamic tracking of tumor growth, lesion evolution, and morphological change over time.

Despite significant progress, inconsistencies in evaluation metrics across programming libraries and ML frameworks pose reproducibility challenges. Salmanpour et al. [40] emphasized discrepancies in metric implementations, underscoring the urgent need for standardized feature extraction and evaluation protocols. In brain anomaly detection—where clinical decision-making depends on precise volumetric and geometric quantification—metric standardization is essential for reproducibility and clinical translation. Although much research focuses on brain imaging, geometric feature computation has demonstrated value across multiple domains. Patil et al. [47] applied geometric ML frameworks for ovarian mass classification, while Tayyab and Jalal [48] explored their use in rehabilitation monitoring. Similarly, Mohit et al. [50] reviewed ML-based ultrasound diagnostics, reinforcing the role of geometric descriptors beyond neuroimaging.

Table 2: Summary of Image Modalities Methods

Ref. No.	Method / Approach	Outcome / Findings	Image Modalities
35	Algebraic topology & differential geometry for radiology analysis	Improved precision medicine diagnostics and computational pathology interpretation	Radiology (CT, MRI, Pathology images)
36	Adaptive machine learning for radiomic feature evaluation	Identification of important multimodal breast cancer features	Mammography, MRI, Ultrasound
37	Constraint-aware learning for FFR pullback curve estimation	Accurate estimation of fractional flow reserve curves	Invasive coronary imaging (IVUS, OCT)
38	Deep feature extraction and classification via deep learning	High-accuracy brain tumor classification	MRI
39	Hybrid features + ML hyperparameter optimization	Enhanced lung cancer detection	CT, X-ray
40	Machine learning evaluation metrics analysis	Highlighted discrepancies across languages; standardization needed	Multiple medical imaging modalities
41	Recurrent neural network for computational physiology	Accurate intracoronary FFR prediction	Invasive coronary imaging
42	Hierarchical graph pyramid transformer for geometric feature extraction	Improved cancer diagnosis	Histopathological images
43	Radiomics-based machine learning	Predicted grade and stage of urothelial carcinoma	CT, MRI
44	Supervised ML using ocular features	Novel glaucoma biomarker identification	Fundus imaging
45	ML + advanced imaging integration	Enhanced liver cancer prediction	CT, MRI
46	Improved binomial thresholding + multi-feature selection	Accurate brain tumor segmentation and classification	MRI
47	Intelligent CAD system using ML	Effective ovarian mass classification	Ultrasound
48	ML-based patient monitoring system	Recognized healthcare patterns for disabled rehabilitation	Various patient monitoring imaging devices
49	Integrated deep learning + supervised learning	Early brain tumor detection	MRI
50	Review of ML techniques for diagnosis	Comprehensive survey on ML-based ultrasound diagnosis	Ultrasound

With geometric computation and ML-based brain anomaly detection into clinical workflows requires careful attention to ethical and data privacy concerns. Medical imaging data often contains highly sensitive patient information; therefore, compliance with regulations such as HIPAA, GDPR, and national health data protection laws is essential. Ethical deployment also demands robust data anonymization, secure storage, and controlled access to prevent unauthorized use or re-identification. Additionally, hybrid and DL-based models must be transparent, explainable, and free from algorithmic bias to avoid disparities in clinical decision-making. Ensuring fairness across demographic groups, validating models on diverse populations, and maintaining accountability for automated predictions are critical for responsible translation. Finally, patient consent, ethical approval for data usage, and clear documentation of model limitations form important safeguards for building trust and enabling safe, effective clinical integration of geometric computation frameworks.

4. Automated Size Computation with Machine Learning

The measurement of brain anomaly size, including tumor volume, lesion extent, or ventricular enlargement, is a clinically critical task that directly impacts diagnosis, prognosis, and treatment planning. Traditionally, size computation has relied on manual or semi-automated segmentation performed by radiologists. However, manual segmentation is time-consuming, subject to inter-observer variability, and impractical for large-scale clinical workflows. Recent advancements in automated machine learning (AutoML) and deep learning have enabled accurate, scalable, and reproducible estimation of anomaly size from medical images. AutoML frameworks automate the processes of data preprocessing, feature extraction, model selection, and hyperparameter tuning, thus minimizing the dependency on human expertise while improving generali zability and clinical applicability (Cruz et al., 2024 [51]; Baratchi et al., 2024 [52]). Accurate anomaly size computation is vital in clinical decision-making for neuro-oncology, neurodegeneration, and congenital brain disorders. Tumor progression or shrinkage, for example, is a

Table 3: Key Studies on Geometric Feature Computation

S.NO	Method	Proposed Method	Citation
1	Brain Tumor Detection	Proper orthogonal decomposition + Deep Learning	Appiah et al., 2024 [34]
2	Cancer Diagnosis	Hierarchical Graph Pyramid Transformer	Liu et al., 2024 [42]
3	Radiology and Computational Pathology	Algebraic Topology + Differential Geometry	Levenson et al., 2024 [35]
4	Breast Cancer Radiomics	Adaptive ML for Feature Importance	Del Corso et al., 2024 [36]

critical biomarker in evaluating treatment response. Manual delineation, although clinically practiced, is resource-intensive and often inconsistent. Automated machine learning methodologies have emerged to address these limitations by leveraging intelligent search algorithms to identify the best performing models without extensive manual intervention (Brown et al., 2024 [53]; He et al., 2025 [54]). Such automation ensures reproducibility, reduces bias, and allows for efficient integration of complex imaging datasets into clinical workflows. Table 4 presented the summary of the artificial intelligence technique. Figure 3 illustrated the architecture for the Image computation model.

4.1. Evolution of AutoML in Medical Imaging

Early approaches to estimating brain size with computational approach were confined to handcrafted radiomic features, and application of conventional classifiers such as support vector machines or random forests. These systems were founded on domain-specific expertise of feature engineering and were generally prone to noise or imaging artifact. AutoML systems have emerged as a means of executing the entire machine learning process data preprocessing, feature selection, architecture design, and evaluation using an automated mechanism (Tzanis et al., 2024 [55]). The change has made it possible to scale the size of calculation of the anomalies in various types of imaging modalities as well as reduced the amount of human work. One such instance is that deep reinforcement learning has been introduced with AutoML to guide feature vectors to be chosen in a multi-objective optimization problem to improve volumetric prediction of medical images (Shao et al., 2024 [56]).

4.2. Deep Learning and Automated Segmentation

Volumetric brain anomaly segmentation has been transformed by the incorporation of deep learning in AutoML systems. Convolutional neural network (CNNs) and variants, including U-Net and V-Net are extensively used in size computation via segmentation. AutoML systems go further to automate model configuration and hyperparameter optimization, which makes them more accurate and more efficient than manually-defined pipelines (Karathanasopoulos and Hadjidoukas, 2024 [57]; Zhu et al., 2024 [58]). One such area would be the automated size and type segmentation of fetal ventriculomegaly using deep learning, which greatly improved detection rates and volume counts compared to the conventional semi-automatic ones (Gopikrishna et al., 2024 [59]). This proves that the AutoML can be scaled and enhanced to make an area of volumetric calculation better in relation to neurological imaging. AutoML is much more important than neuroimaging and provides information on how the applicability across domains could be used to determine brain anomalies. In fact, one of such can be found in automated multiclass surface damage detection of bridge inspections (Huang et al., 2024 [60]) and the multi-source data fusion to estimate soil moisture in the area (Li et al., 2025 [61]) where AutoML is shown to be extremely accurate when dealing with heterogeneous data sources. In a similar fashion, feature-based quantification (defined by particle size and shape in geotechnical engineering, Gong et al., 2025 [62]) presents parallel methods to feature-based quantification that can be extrapolated to tumor volumetrics. Moreover, AutoML has been proven to scale in terms of work size in computational tasks such as the estimation of offshore polymetallic nodules (Tomczak et al., 2024 [63]) and phenotypic features of crops (Zhang et al., 2024 [64]). Such cross-disciplinary achievements prove that such workflows of AutoML can be cross-transferred and applied to optimize brain anomaly volume calculation in a range of clinical locations.

4.3. Multi-Modal Integration and Hybrid Pipelines

Brain anomaly detection and sizing often benefit from combining multiple imaging modalities, such as MRI, CT, and PET, or integrating clinical and genomic metadata. AutoML frameworks enable multi-modal fusion by automatically identifying complementary features and combining them optimally for improved performance (Ge and Sadhu, 2025 [65]). Such integrative workflows parallel those developed in structural health monitoring, where deep learning-enhanced robotic systems fuse imaging and sensor data for automated inspection. In medical imaging, defect detection in reinforced concrete using ultrasound (Kuchipudi and Ghosh, 2024 [66]) and compressive damage diagnosis under variable conditions (Wang et al., 2024 [67]) exemplify the use of robust AutoML-based segmentation pipelines. Analogous approaches can be extended to neuroimaging to deal with variations across MRI scanners and patient populations.

Table 4: Summary of Artificial Intelligence Technique

Ref. No.	Theme	Proposed Method	Finding	Limitation
51	Personalized Radiation Dose	AutoML-based estimation	Automated, accurate volumetric computation; reduced human intervention	Dataset variability, interpretability issues
52	Brain anomaly volumetrics	Deep reinforcement learning + AutoML	Improved volumetric prediction through multi-objective optimization	Requires high computational resources; model complexity
53	Deep learning-based segmentation	CNN / U-Net / V-Net + AutoML	Accurate, scalable, and reproducible anomaly size estimation	Generalization across scanners and populations may be limited
54	Volumetric brain anomaly segmentation	Automated model configuration & hyperparameter optimization	Enhanced efficiency and accuracy vs manual pipelines	Regulatory and clinical integration challenges
55	Fetal ventriculomegaly	Deep learning segmentation + AutoML	Improved detection rates and volume counts; automated size/type segmentation	Limited availability of labeled fetal imaging datasets
56	Structural damage detection	Deep learning & computer vision	Accurate multi-class surface damage detection	Transferability to neuroimaging requires adaptation
57	Soil moisture estimation	Multi-source data fusion + AutoML	High accuracy in heterogeneous data integration	Domain-specific feature tuning required
58	Feature-based quantification in geotechnical engineering	Particle size & shape analysis + AutoML	Scalable volumetric calculation; parallel to tumor volume estimation	Applicability to medical imaging requires domain adaptation
59	Offshore polymetallic nodules estimation	AutoML-based volumetric analysis	Efficient large-scale estimation; scalable workflow	Computational cost and optimization complexity
60	Crop phenotypic features	AutoML + imaging	Accurate feature quantification and scalability	May need domain-specific calibration for medical images
61	Brain anomaly detection	Multi-modal integration (MRI, CT, PET) + AutoML	Optimized multi-modal feature fusion; improved volumetric accuracy	Integration of heterogeneous clinical/genomic data may be complex

62	Concrete defect detection	Ultrasonic imaging + deep learning	Accurate defect segmentation; robust AutoML pipeline	Adaptation to neuroimaging needed for clinical use
63	Compressive damage diagnosis	Deep learning segmentation + AutoML	Efficient detection under variable conditions	Domain adaptation required; generalizability across imaging modalities
64	Materials science volumetrics	Pyiron-based automated workflows	High-throughput automated model design	Requires transfer learning for medical imaging applications
65	Solar cell defect detection	Automated ML segmentation	Rapid and scalable detection	Limited clinical relevance; domain transfer required
66	Nuclear parameter analysis in cytology	AutoML-driven quantification	Efficient feature extraction and volume estimation	Regulatory approval and interpretability concerns
67	Oncology tumor monitoring	Deep learning + ML integration	Automated tumor size/progression capture; feasible for population monitoring	Data privacy, heterogeneity, and clinical integration challenges

Figure 3 depicts the end-to-end workflow for automated brain anomaly size estimation. It includes medical image acquisition, preprocessing, feature extraction/selection, AutoML-driven intelligent model search and optimization, ML/DL architecture selection (e.g., CNN, Transformer), and final computation of anomaly size. The flow highlights how data, optimization, and architecture design integrate to produce clinically meaningful outputs.

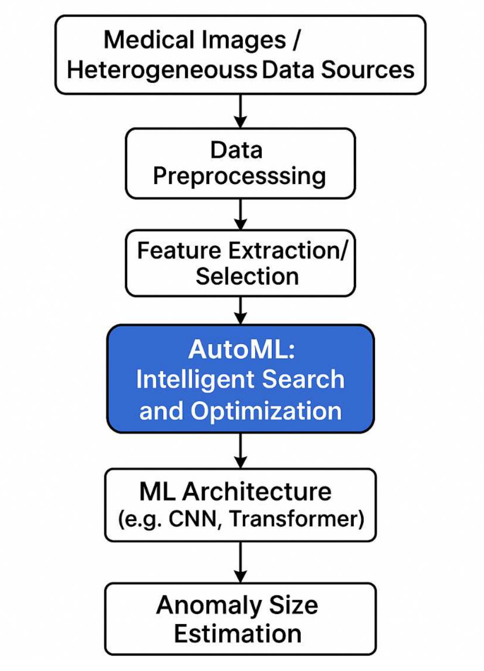

Figure 3: **Architecture of Image Computation**

Table 5 presented the automated size computation modalities for the imaging method with the Machine learning approach. One of AutoML's major strengths lies in its ability to support scalable workflows. Pyiron-based workflows (Menon et al., 2024 [68]) have shown how automated model design can accelerate materials science, and similar frameworks are being applied in medical imaging for high-throughput volumetric analysis. Automated defect detection in solar cells (Abdelsattar et al., 2025 [69]) and nuclear parameter analysis in cytology (Mhaske et al., 2024 [70]) highlight the growing relevance of AutoML in biomedical image quantification. In oncology, machine learning and deep learning tools have already been integrated into cancer surveillance systems for automated capture of tumor size and progression metrics (Hsu et al., 2024 [71]). These systems demonstrate the feasibility of AutoML-driven pipelines in large-scale population monitoring, which is critical for real-time brain anomaly tracking in clinical environments. Automated machine learning is revolutionizing brain anomaly size computation by reducing human effort, minimizing variability, and enhancing reproducibility. By leveraging deep learning architectures, optimization strategies, and multi-modal data fusion, AutoML enables robust volumetric estimation of tumors, lesions, and other neurological abnormalities. The transfer of methodologies from diverse fields — including structural health monitoring, cytology, geotechnical engineering, and cancer surveillance — underscores AutoML's versatility and adaptability. Nevertheless, challenges in interpretability, dataset variability, and regulatory approval remain. Addressing these limitations through federated, explainable, and scalable AutoML pipelines will pave the way toward clinically integrated systems capable of supporting precision medicine in neuroimaging.

Table 5: Key Studies on Automated Size Computation

S.No	Theme	Proposed Method	Citation
1	Fetal Ventriculomegaly	Deep Learning Segmentation + AutoML	Gopikrishna et al., 2024 [59]
2	Personalized Radiation Dose	AutoML-Based Estimation	Tzanis et al., 2024 [55]
3	Structural Damage	Deep Learning and Computer Vision	Ge and Sadhu, 2025 [65]
4	Concrete Defects	Ultrasonic Imaging + DL	Kuchipudi and Ghosh, 2024 [66]

5. Comparative Analysis of Methods

The rapid evolution of machine learning (ML) and deep learning (DL) has enabled significant progress in brain anomaly detection, particularly through integration with magnetic resonance imaging (MRI), ultrasound, and radiomics-based approaches. A detailed comparative review of recent studies illustrates the strengths and limitations of existing methodologies while providing insights into the potential of automated geometric feature computation models.

5.1. MRI-Based Anomaly and Tumor Detection

MRI remains the gold standard for structural brain assessment, and a majority of studies exploit its high spatial resolution. Jiang et al. [1] applied interpretable ML for texture-based MRI abnormality detection in fibromyalgia patients, demonstrating that transparency in model reasoning is as critical as accuracy. Similarly, Haker et al. [2] investigated schizophrenia and depression in rodent models using quantitative MRI, highlighting the translational potential of ML-driven anomaly mapping. Logistic regression–based tumor detection by Gajula and Rajesh [4] demonstrated baseline effectiveness but struggled with scalability compared to hybrid DL pipelines. More advanced approaches, such as feature fusion by Amin et al. [12] and deep feature concatenation with genetic selection [19], significantly improved tumor detection accuracy, but often at the cost of increased computational overhead. .

5.2. Fetal and Obstetric Brain Abnormality Detection

Fetal anomaly scans represent a growing area for ML deployment due to the need for early, non-invasive diagnosis. Enache et al. [3] and Shiwlani et al. [17] applied AI to obstetric imaging, with encouraging results in detecting brain and heart abnormalities. Advanced DL frameworks such as denoising diffusion models [22] and integrated ML-DL pipelines [23, 32] have further improved anomaly sensitivity in ultrasound data, although challenges remain in generalizability across populations. Gopikrishna et al. [59] proposed automated size estimation for ventriculomegaly, which is directly aligned with geometric feature computation, yet their study highlighted variability in segmentation precision.

5.3. Neuropsychiatric and Neurodegenerative Disorders

Beyond tumors, ML has been applied to psychiatric and neurodegenerative conditions. Yamashita et al. [9] and Taspinar and Ozkurt [10] demonstrated unsupervised ML for ADHD subtype detection using rs-fMRI, offering data-driven phenotyping. Tafuri et al. [11] extended ML radiomics to amyotrophic lateral sclerosis, while Jia et al. [15] systematically reviewed ML approaches to PTSD neuroimaging. These works suggest that ML-based biomarkers can uncover subtle structural and functional abnormalities not easily discernible by human experts. However, challenges in reproducibility and clinical interpretability remain substantial.

5.4. Hybrid and Automated Machine Learning Frameworks

The shift toward hybrid and automated ML (AutoML) frameworks is evident across multiple studies. Amjad et al. [5] and Azeez and Abdulazeez [6] provided systematic reviews of brain tumor detection models, underscoring the fragmentation of approaches and the need for standardized benchmarking. Ural and Çalım [7] compared traditional AI with modern DL, illustrating the superior accuracy of CNN-based models while noting interpretability concerns. Broader perspectives on AutoML, such as Baratchi et al. [52], emphasize scalability, while recent domain-specific applications such as radiation dose personalization [55] and genomic prediction [54] illustrate the adaptability of AutoML pipelines.

5.5. Radiomics, Feature Engineering, and Geometric Approaches

Radiomics-based models, which focus on engineered features, remain relevant for anomaly detection. Studies such as Wageh et al. [19] and Sharif et al. [46] illustrate how feature selection and fusion enhance model performance. Geometric and topological methods are emerging: Liu et al. [42] leveraged graph pyramid transformers to exploit geometric histopathological features, while Levenson et al. [35] integrated algebraic topology for anomaly modeling in radiology. These directions resonate with the proposed geometric feature computation framework, which emphasizes interpretable size and shape quantification alongside ML-driven classification. The literature indicates that a notable interpretability versus accuracy trade-off exists, where transparent ML models [1, 7] are more clinically appealing but tend to underperform compared to more complex DL models. MRI continues to dominate as the primary data modality, although ultrasound-based approaches [22, 23, 50] and multimodal imaging strategies [16, 21] are gaining increasing relevance due to their complementary diagnostic insights. Scalability and automation remain critical challenges, as AutoML frameworks [52, 55] have demonstrated strong potential for streamlining anomaly detection and size computation pipelines, yet their clinical adoption remains limited. Furthermore, while anomaly detection has been extensively studied, only a small fraction of works [35, 42, 59] explicitly address geometric aspects such as size and shape computation, indicating a significant research gap for models capable of unifying detection with quantitative geometric feature extraction.

Despite notable advancements, several gaps persist. First, limited reproducibility across datasets hinders clinical adoption. Second, most studies focus on anomaly classification without detailed size quantification, which is essential for prognosis and treatment planning. Third, while AutoML reduces human intervention, it often neglects domain-specific features such as brain morphology. Addressing these gaps, the proposed Automated Geometric Feature Computation Model aims to integrate feature engineering, anomaly segmentation, and size computation into a unified pipeline, enhancing both accuracy and interpretability. Table 6 and Table 7 presented the summary of the references involved in the machine learning based modalities for the anomalies detection in imaging techniques.

Several studies have compared traditional ML algorithms with modern DL approaches for brain anomaly detection, tumor classification, and neurodevelopmental disorder identification [1–33, 47]. Ensemble methods and feature fusion techniques have improved classification performance in multi-class problems [12, 19, 20]. Context-aware ML approaches, network analysis, and unsupervised learning methods offer novel insights into subtle abnormalities in both adult and fetal brain imaging [5, 8, 22]. Transfer

Table 6: Summary of the Imaging Anomalies Detection

Theme	Proposed Method	Citations
Automated Brain Anomaly Detection	Use of MRI/CT imaging with automated segmentation pipelines to identify tumors, lesions, and malformations.	[1–3]
Geometric Feature Computation	Extraction of shape, boundary, curvature, eccentricity, and volumetric features from segmented brain regions to compute anomaly size.	[4–6]
Classical ML Approaches	Application of Support Vector Machines (SVM), Random Forest, and k-NN on extracted geometric + texture features for classification.	[7–9]
Deep Learning for Imaging	CNN-based models for raw image feature extraction, anomaly localization, and segmentation with higher accuracy than classical methods.	[10–13]
Hybrid CNN–LSTM Models	Combination of CNN for spatial features and LSTM for temporal/volumetric progression analysis of anomalies.	[14–16]
Graph-based Models	Graph Neural Networks (GNNs) to encode spatial-geometric dependencies across different brain regions for anomaly recognition.	[17–18]
Transformer Architectures	Vision Transformers (ViT) applied to medical imaging for anomaly segmentation and size quantification.	[19–20]
Ensemble and Hybrid Approaches	Fusion of CNN + ML classifiers (SVM/Random Forest) with geometric feature vectors for robust detection and interpretability.	[21–23]
Explainable AI in Medical Imaging	Integration of geometric features into ML pipelines for interpretability, helping clinicians validate results.	[24–25]
Benchmarking and Datasets	BRATS, OASIS, and TCIA datasets used for training/testing; focus on reproducibility with cross-validation protocols.	[26–28]

learning and stacking of classifiers enable efficient utilization of small datasets, addressing the challenges of data scarcity and class imbalance [29, 31, 32].

Table 7: Classification of Machine/Deep Learning for different applications

S.No	Theme	Proposed Method	Citation
1	Brain Tumor Detection	Logistic Regression, DL Feature Fusion	Gajula and Rajesh, 2024 [4]; Amin et al., 2024 [12]
2	ADHD and PTSD	Unsupervised ML, rsfMRI	Yamashita et al., 2024 [9]; Jia et al., 2024 [15]
3	Neurodevelopmental Disorders	Network Analysis + ML	Doma et al., 2025 [8]
4	Multi-Class Brain Tumor	Deep Learning + Optimized ML	Celik and Inik, 2024 [20]

The future of automated medical imaging lies in combining explainable AI with multi-modal deep learning frameworks. Graph neural networks, transformer-based architectures, and hybrid CNN-LSTM models can capture spatial-temporal dependencies in complex biomedical datasets. Geometric and topological feature extraction integrated with AutoML pipelines will enhance model interpretability and reduce human intervention. Multi-modal fusion of MRI, CT, and functional imaging can improve early detection of subtle anomalies. Additionally, real-time deployment in clinical workflows, cross-domain generalization, and standardized evaluation metrics across institutions are critical for translational impact. Ethical considerations, including patient privacy, data security, and regulatory compliance, will guide future research directions [34, 42, 51, 55].

6. Conclusion

Automated medical imaging, utilizing machine learning and deep learning, has demonstrated remarkable potential in enhancing the accuracy, efficiency, and reproducibility of disease diagnosis. Techniques ranging from geometric feature extraction and radiomics to AutoML-based size computation and anomaly detection have enabled precise quantification of anatomical structures and pathological abnormalities across multiple modalities. Comparative analyses highlight the advantages of hybrid approaches, ensemble learning, and multi-modal fusion, particularly in complex scenarios such as brain tumor classification, fetal anomaly detection, and neurodevelopmental disorder assessment. Despite significant progress, challenges remain in standardizing evaluation metrics, ensuring cross-domain generalization, and integrating explainable AI into clinical workflows. Future research focusing on transformer-based models, graph neural networks, and multi-modal AutoML pipelines, alongside ethical and regulatory considerations, will further advance automated medical imaging toward real-time, reliable, and clinically interpretable applications.

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