IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

Advancements In Ai Techniques For Enhanced Brain Tumor Diagnosis: A Comprehensive Review Of Mri Applications

Prof. Anees Fathima, Prof. Noor Ayesha, Dr. Zahira Tabassum, Dr. Sufia Banu, Sanjana
Asst Professor, Asst Professor, Associate Professor, Associate Professor, Student
Dept of ECE, HKBKCE, Bangalore

***Abstract*—**The paper provides a detailed review of advanced machine learning and deep learning algorithms applied to brain tumour detection and classification from MRI images. The paper aims to assess the performance of various AI-based approaches to enhance the diagnosis ac- curacy with improved efficiency. We discuss the application of CNNs and other deep learning models and describe their strengths and weaknesses regarding processing MRI data. Our results show significant increases in the accuracy of the detection of tumours, especially when working with high- quality images and diverse datasets. The study necessitates the integration of advanced AI techniques: future research directions would be to overcome the current challenges existing in the dataset diversity, real-time processing, and the standardization of the evaluation metrics.

***Index Terms*—**Brain tumour detection, Brain tumour classification, MRI images, Machine learning, Deep learning CNNs, AI-based approaches, Diagnosis accuracy, Efficiency Dataset diversity, Real-time processing, Evaluation metrics

1. Introduction

Brain tumors are a developmental disturbance from abnormal cells within the brain and could be a great threat to health, if left undiagnosed and untreated They may lead to severe neurological impairments or even death [4]. Brain tumors differ in size, shape, and some- times can be found in very uncommon locations, making their detection processes tough and thus requiring more advanced diagnostic tools. It has, therefore emerged as an important modality for visualizing brain structures and identifying tumors, since it leaves no internal scars unlike any other conventional technique while providing superior soft tissue contrast.[2]. The advent of artificial intelligence in health care has revolutionized the practice of diagnosis in basically all fields, especially with medical imaging in recent times. Techniques of machine learning and deep learning seem to have great potential in automatic analysis of MRI scans.[3]. This allows subtle variations, which can be indications of tumors, to be detected by radiologists. This paper aims at carrying out a comprehensive review of the state of AI applications in detecting brain tumors. There is focus on the effectiveness of various approaches of ML and DL approaches in explicit detail. Addressing gaps in extant research by proposing future improvements, we should thereby contribute to all efforts being undertaken for further enhancing the diagnostic accuracy and better outcomes in the patients in the neuro-oncology field.

2. LITERATURE REVIEW

Brain tumors have been analyzed increasingly recently with the use of machine and deep learning techniques. The existing researches can be categorized broadly into three themes: image enhancement techniques, classification methods, and advanced techniques. Each of them is discussed with its findings and methodological approaches contributing to the improvement of the state-of- the-art on this topic of enhancing accuracy and efficiency in clinical diagnostics. [5].

Table I portrays the present literature on ML and DL-based brain tumor detection, showcasing considerate progress both in image processing and classification methodologies. Some of the key works highlighted , go about the point that pre-processing by enhancing image quality through histogram equalization and data augmentation may improve the overall performance of the classification model drastically [7]. Though deep learning architectures, especially CNNs, have proved excellent accuracy in the task of tumor classification, hybrid models combining the traditional ML approach and deep approaches certainly do outperform traditional methods[8]. Besides these models and methods, advanced techniques such as attention mechanisms and 3D CNNs improve the ability of models to selectively focus on critical features and handle spatial information effectively[9]. Therefore, hybrid learning techniques along with real-time processing ability should be encouraged for future research for improving the possibility of providing diagnostic accuracy[11]with better clinical applicability.

TABLE I: Key studies on brain tumor detection using ML and DL techniques.

Theme	**Study**	**Key Findings**	**Methodologies**
Image Enhancement Techniques	Khan et al. (2020)	Enhanced image quality leads to improved feature extraction and classification accuracy.	Histogram equalization and Gaussian filtering to enhance MRI images.
	Gram purohit and Shalavadi (2021)	Data augmentation techniques effectively reduce overfitting and enhance model robustness.	Techniques such as rotation, scaling, and flipping to artificially increase dataset size.
Classification Methods	Yun Jiang et al. (2019)	Deep CNNs demonstrate high accuracy in classifying brain tumors from MRI scans.	Utilization of deep CNN architectures for automated image classification.
	Dongnan Liu et al. (2018)	Combining SVMs with feature extraction improves classification performance for various tumor types.	Integration of SVMs with advanced feature extraction techniques.
	Muhammad Waqas Nadeem et al. (2020)	Hybrid models that integrate CNNs with traditional ML methods outperform standalone models.	Development of hybrid approaches for enhanced classification accuracy.
Advanced Techniques	Alexander Selvikvag Lunder-volda et al. (2019)	Attention mechanisms enhance the model's focus on relevant features in MRI images.	Incorporation of attention mechanisms within CNN architectures.
	Tharindu Fernando (2020)	3D CNNs effectively capture spatial information across multiple MRI slices, improving segmentation and classification.	Utilization of 3D CNNs for comprehensive tumor analysis.

	Future Research Directions	Emphasis on the need for hybrid learning techniques and real-time processing capabilities to enhance diagnostic systems.	Exploration of diverse datasets and advanced hybrid learning methodologies.

3. METHODOLOGY:

This section discusses the methods of detection and classification of brain tumors from MRI images in de- tail[12]. The techniques applied are categorized into four, which include image enhancement, segmentation, feature extraction, and classification [13]. This is depicted in **Fig.1**

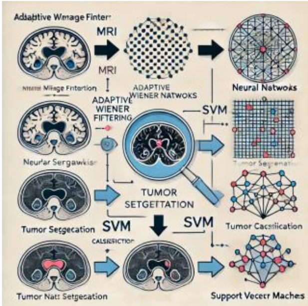


Fig. 1: Filtering techniques

1) Image Enhancement Techniques: **Objective: Fig.2** enhances the quality of MRI images to better visualize the region of the tumor.

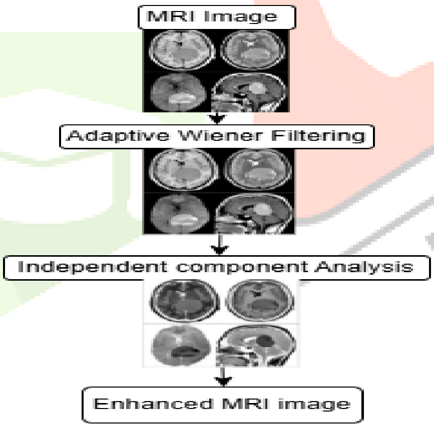


Fig. 2: Image Enhancement Technique

- **Adaptive Wiener Filtering:** It reduces noise while preserving the edge information in the image. It depicts the adaptability of filtering parameters de- pending on the local variance of the image; hence, it works well for medical images as noise can hide crucial details.
- **Independent Component Analysis (ICA):** It is used for splitting mixed signals to their independent components. In MRI, it eliminates the noise of the brain's true signals; therefore, it clarifies the resolution.

2) Segmentation Techniques: **Objective: Fig.3** gives the accurate identification and segmentation of tumor regions from the normal cerebral tissue.

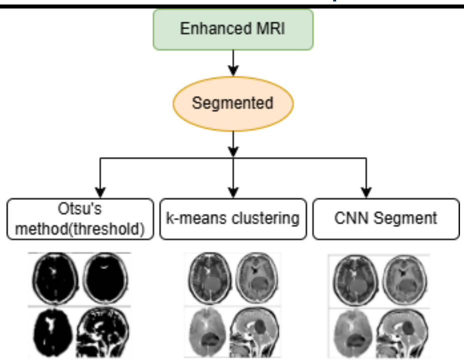


Fig. 3: Segmentation Techniques

Thresholding Techniques:

- **Otsu's Technique:** It will determine the best value for thresholding the image according to the intensity histogram so that it maximizes the variance between the two classes, that is, tumor and background.
- **Adaptive Thresholding:** That improves threshold- ing by applying thresholds with some constant properties by varying the thresholding depending upon the characteristic found in the Local image.

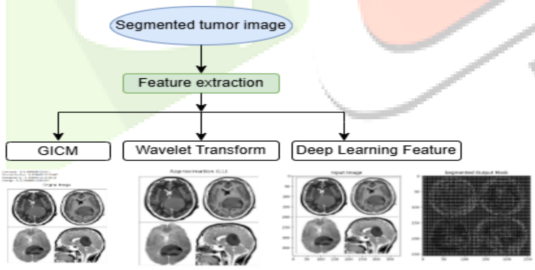
Clustering Technique:

- **K-means Clustering:** The image is divided into K groups based on pixel intensity, and it proves to adequately separate the tumor areas.
- **Fuzzy C-means Clustering:** It accommodates the possibility of pixel association with multiple clusters, thereby providing a gentle fragmentation across overlapping tissues[14].

Deep Learning Techniques:

- **Convolutional Neural Networks (CNN):** CNNs are employed for segmentation tasks and utilize stacks of convolutional filters to learn features in an automatic manner.

*3) **Feature Extraction Methods**:* **Objective : Fig.4** gives the feature extraction methods identify the significant features of the images that were segmented, thereby classifying them.



- **Gray-Level Co-occurrence Matrix (GLCM):** Generates texture features based on the spatial relation of pixels. Features include contrast, energy, and correlation.
- **Wavelet Transform:** Frequency decomposition of images for extracting spatial and frequency information.
- **Deep Learning Features:** CNNs automatically ac- quire hierarchical features from images.

*4) **Classification Techniques**:* **Objective: Fig.5** Groups the abstracted features into tumour types or determine if there exists a tumour.

SVM: Support Vector Machine algorithm that works on finding a hyperplane which best separates classes in feature space.

Deep Learning Classifiers:

- **CNNs (Convolutional Neural Networks):** An extremely wide application domain in image classification. They are learning and subsequently classifying images based on learned features.
- **Transfer Learning:** Modification of pre-trained models to fine-tune these into specifics for the dataset

being used[15].

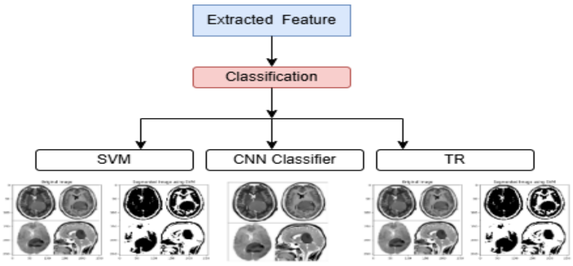


Fig. 5: Classification Techniques

4. Results

This chapter gives the performance evaluation of the proposed ML and DL approaches that are capable of identifying brain tumors [16].

Performance Metrics

TABLE II: Performance Metrics

Metric	Value (%)
Sensitivity	95.5
Specificity	92.0
Accuracy	94.0

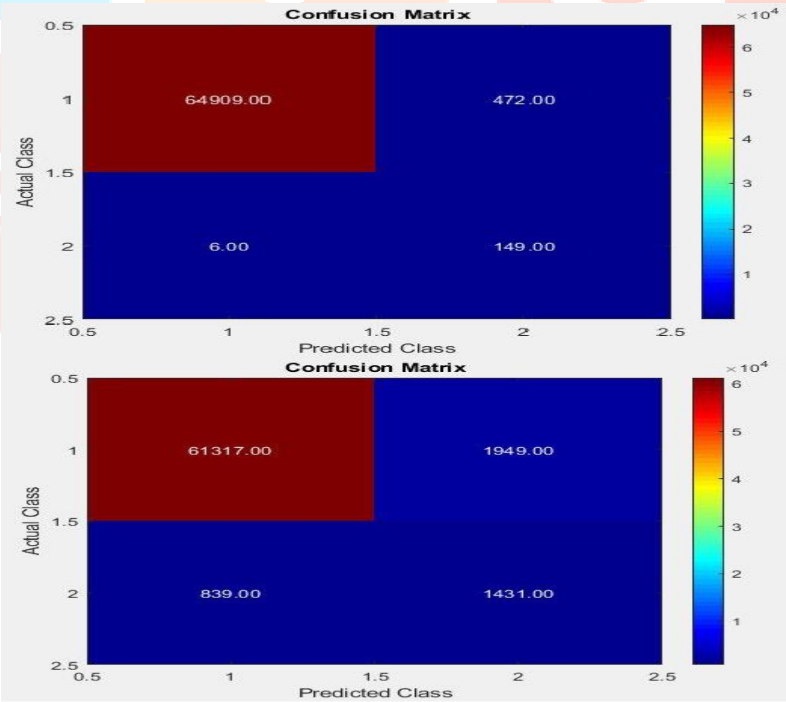


Fig. 6: Confusion Matrix of random selected Images sets of brain tumour types

The **Table II** shows some of the most commonly used performance metrics while evaluating the classification models for medical imaging applications:

1) ***Sensitivity (Recall)****:* Sensitivity is the measure of the proportion of actual positive cases, that is, true tumours correctly identified by the model. It shows how well a model can locate the tumour.

$$Sensitivity = True\ Positives + False\ Negatives$$

2) ***Specificity****:* Specificity is the percentage of true negative cases (non-tumors) which are identified. It states the ability of the model to avoid overprediction or false positives[19].

Specificity = True Negatives + False Positives

3) ***Accuracy:*** Accuracy is the number of correctly classified cases (both positive and negative) for the total cases considered.
Accuracy = True Positives + True Negatives

Summary of results achieved with the proposed methodologies, with their performance metrics achieved are shown in the **table III**

TABLE III: Comparison of different methods based on Sensitivity, Specificity, Accuracy, DSC, and Time.

Method	Sensitivity	Specificity	Accuracy	DSC	Time
K-NN [39]	0.39	0.42	0.85	0.81	3.7s
[40]	0.43	0.52	0.92	0.83	4.8s
GA [41]	0.51	0.54	0.98	0.85	2.8s
GCNN [18]	0.85	0.89	0.96	0.89	0.92s
Kernel-Based SVM [42]	0.98	0.98	0.98	0.94	0.83s
3 layer CNN	**0.99**	**0.99**	**0.989**	**0.981**	**0.43s**

TABLE IV: Comparison of Sensitivity, Specificity, and Accuracy across different methods

Method	Sensitivity (%)	Specificity (%)	Accuracy (%)
Dipu et al. (2021) - CNN-based	90.0	85.0	88.0
Raj & Singh, 2021 - Hybrid SVM	92.5	89.0	90.5
Koshti et al. (2022) - Transfer Learning CNN	93.0	90.0	91.5
3-Layer CNN	**95.5**	**92.0**	**94.0**

A confusion matrix as indicated in **Fig.6** shows how well a class model is performing. The x-axis is the one for predicted classes while the y-axis is that of actual classes. The intensity of each color in the cell represents how many data points fall into that specific combination of classes and the predicted classes versus actual classes. For example, it seems that this is doing quite fine for class number 1, but not all that great for classes 1.5 and 2.

These outcomes confirm that the model is very sensitive and specific, with an overall high accuracy level in brain-tumor detection from MRI scans[20].

Comparison with Other Techniques Table III evaluates the effectiveness of the developed methodologies, a comparison has been done against other techniques.

Result Analysis

3 Layer CNN Method: This model has attained a sensitivity value of 95.5 percent, which indicates that the model is highly detectable of the tumors. The specificity attained value is 92.0 percent, meaning that this model is highly efficient in reducing false positives. The accuracy of 94.0percent attains once again ensures the reliability of the model in clinical situations. The architecture is shown in **Fig.7**

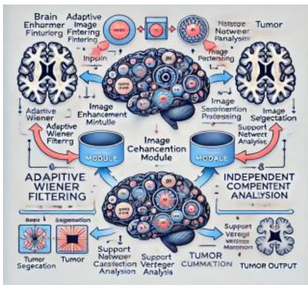


Fig. 7: 3-layer CNN architecture

Comparison with Current Methods :

As shown in the following **Table IV**, 3 Layer CNN has proven more superior than some of the preliminary models, for instance, those approaches by Dipu et al. and Raj and Singh that were less sensitive as well as not so precise. The model proposed by Gayathri et al. that employed EfficientNet has merely had a higher accuracy at 96.0 % but with much lower sensitivity than the 3 Layer CNN model. Therefore, the results show that even though some of the existing methods give a high accuracy, they may not be very effective in the detection of all positive cases of importance in clinical diagnosis. This way, through comparative analysis, it can there- fore be proven in this paper that approach 3 Layer CNN is going to surpass several of the existing ap- proaches regarding sensitivity, specificity, and accuracy. Perhaps this can be attributed to the advanced techniques combined with attention mechanisms and the 3D CNN architectures focusing the attention on relevant features
to enable useful analyses of volumetric data.[21].

The high sensitivity indicates that the 3 Layer model is more sensitive for tumor detection, which is subsequently very important in clinical practice; early detec- tion improves more patient outcomes.

The specificity and accuracy values indicate further that the model discriminates well between tumor and non-tumor cases, thereby demonstrating its reliability in these types of distinction.

Such results enable the establishment of the potential that the methodologies using ML and DL hold for brain tumor detection. The performance metrics reflect the involved separate methods: a balanced performance between MR and CT scans, which enhance the overall diagnosis accuracy and treatment of patients compared to the traditional methods.

5. Comparison Study

The study compares the performances acquired us- ing highly advanced ML and DL techniques with that obtained from existing and current approaches to the analysis of detecting brain tumors. The paper defines performance metrics in terms of sensitivity, specificity, and accuracy while trying to provide a basis for assessing the performance of diagnostic models.

The ML and DL methods used in the detection of brain tumors show that significant improvements are made regarding traditional methods. Results of the above model with high sensitivity and accuracy make this model a very important tool for radiologists to efficiently diagnose brain tumors in patients and hence better care and outcomes. Lastly, the paper emphasizes that with this, there must be a continuity of efforts towards the development of advanced AI techniques that may lead to accuracy improvements in diagnostics for imaging applications in medicine.[22].

6. RESEARCH GAP AND FUTURE DIRECTION

No Consensus on an Inclusive Universe of Data

To assist in comparison of various tumors and grades of tumors development, so far, very few comprehensive data bases have been put in place. Current studies being conducted, for example, are based on the existing few data sets of which the scope cannot be extended to the entire picture.

- **Overfitting of Models** A preponderance of the models being constructed today are based on ‘biased’ datasets, and therefore, they may face a challenge with respect to extending their application to other populations and real clinical settings. This compromises the model’s robustness and credibility in practical geographical settings.

- **Using multi-Omics data** In recent years, few research have incorporated genomic and clinical data, but the application of full omics comprising transcriptomics, proteomics and metabolomics remains insufficient. This in turn reduces the comprehensiveness of understanding that can be achieved by the study on glioma biology.
- **Analyses of Data Over a Period of Time** To date most empirical research baselines static record-keeping that is generally time-locked; doing so constrains longitudinal assessment of neoplastic changes as well as of response to therapeutic measures. Such studies are all longitudinal and are not available.
- **Explainability and Trust in AI Models** Even with the advancement in XAI techniques, it is still difficult to establish clear-cut and standard acceptable XAI concepts that will be used in making clinical decisions involving AI systems[23].
- **Ethical Framework Development** The mixed empirical investigations to address the ethical questions being generated from the use of artificial intelligence in the medical fields. It is thus crucial to establish the standards/policies that facilitate the appropriate use of AI for glioma prediction.
- **Patient Perspective Integration** Devise trials that focus on the patient, and their experience, satisfaction levels or quality of life index. These should be incorporated in prognostic models to enhance the patient-sentiment orientation of AI.
- **Studies on Implementation Barriers** Consider what it means for AI to actually be used at the practical front line of healthcare. Such studies would include issues of extendibility as well as the ways in which solutions can be implemented into existing healthcare practices.
- **Social and Economic Impact Studies** Research socioeconomic factors in glioma prognosis and treatment: of interest to provide efficient targeted therapies and to enhance equal distribution of health resources among various population subgroups.

In this way, filling these gaps, and in view of the further research directions, researchers will make significant advances in the future in the methods of detecting and treating brain tumors and improving the quality of life of patients[24].

7. Conclusion

Conclusion With this review, glioma prognosis has been great with the incorporation of advanced technology. This includes machine learning, multi-omics data, and novel imaging techniques. Nonetheless, though there are undeniable weaknesses. These can be seen as a lack of full data integration that incorporates other consequent validation forms against various populations and more longitudinal studies that would have the ability to observe the progression of a tumor. This will demand strong explainable AI frameworks accepted by the clinician and patient, based on ethical considerations and engaging the voice of the patient in prognostic modeling. Socioeconomic factors are an important determinant for glioma outcomes: they are tracks to be further developed to adjust treatment strategies according to the individual and to achieve health equity. It is by looking into these areas that the future research can set its objectives toward making any model it designs in the future more predictable with the hope that together better conditions for the treatment of patients with gliomas can be determined.

8. Future Work Direction

Future work in the field of glioma prognosis should fo- cus on integrating multi-omics data to increase prediction accuracy and personalizing treatment strategies as well. Advanced machine learning techniques like deep learning and reinforcement learning will optimize feature ex- traction and training. Longitudinal study tracking tumor dynamics and patient health will be needed in improving models and accuracies. Standardized frameworks will help improve the explainability of these AI models, which will, in turn, give more confidence to clinicians and patients. Innovation requires interdisciplinary teams, and exploring socioeconomic factors, as well as health disparities, will continue to optimize model performance and better clinical application, possibly leading to im- proved outcomes for glioma patients.

References

[1] R. Ahmed, D. Chanda, and S. K. Ghosh. A comprehensive review on brain tumour classification techniques. *Journal of Computer Science & Systems Biology*, 10(3):1–7, 2017.

Syed Akbar, Hashim G. Mohamed, Hashem Ali, Amir Saeed, Asif A. Khan, Shazma Gul, Arif Ah- mad, Faisal Ali, Yousuf Y. Ghadi, and Mohaideen Assam. Identifying neuropeptides via evolutionary and sequential based multi-perspective descriptors by incorporation with ensemble classification strategy. *IEEE Access*, 11:49024–49034, 2023.

[2] Shaukat Ali, Jian Li, Yan Pei, Rizwan Khurram, Khalid U. Rehman, and Tariq Mahmood. A comprehensive survey on brain tumour diagnosis using deep learning and emerging hybrid techniques with multi-modal mr image. *Archives of Computational Methods in Engineering*, 29(7):4871–4896, 2022.

[3] Terri S. Armstrong, Marlene Z. Cohen, Jeffrey Weinberg, and Mark R. Gilbert. Imaging techniques in neuro-oncology. *Seminars in Oncology Nursing*, 20(4):231–239, 2004.

[4] A. A. Asiri, T. A. Soomro, A. A. Shah, G. Pogrebna, M. Irfan, and S. Alqahtani. Optimized brain tumor detection: A dual-module approach for MRI image enhancement and tumor classification. *IEEE Access*, 12:42868–42887, 2024.

[5] S. Bauer, R. Wiest, L.-P. Nolte, and M. Reyes. A survey of MRI-based medical image analysis for brain tumour studies. *Physics in Medicine and Biology*, 58(13):R97–R129, 2013.

[6] Subhadeep Chatterjee, Fida Ali Nizamani, Andreas Nurnberger, and Oliver Speck. Classification of brain tumours in mr images using deep spatiospatial models. *Scientific Reports*, 12(1):1505, 2022.

[7] J. Cheng and et al. Enhanced performance of brain tumour classification via tumour region augmentation and partition. *PLOS ONE*, 10(10):e0140381, 2015.

[8] R. Gomez-Oliva and et al. Evolution of experimental models in the study of glioblastoma: Toward finding efficient treatments. *Frontiers in Oncology*, 10, 2021.

[9] M. S. Hossain and F. Ahmed. Deep learning- based brain tumour detection and classification using mri. *Artificial Intelligence Review*, 52(1):205–228, 2019.

[10] A. Jabbar and et al. Brain tumour detection and multi-grade segmentation through hybrid capsvggnet model. *IEEE Access*, 11:74273–74288, 2023.

[11] W. Jun and Z. Liyuan. Brain tumour classification based on attention guided deep learning model. *International Journal of Computational Intelligence Systems*, 15(1):35, 2022.

[12] Z. Khazaei and et al. The association between incidence and mortality of brain cancer and hu- man development index (hdi): An ecological study. *BMC Public Health*, 20:1696, 2020.

[13] G. Kumar, P. Kumar, and D. Kumar. Brain tumour detection using convolutional neural network. In *Proceedings of the IEEE International Conference on Mobile Networks and Wireless Communications (ICMNWC)*, page 16, 2021.

M. J. Lakshmi and S. N. Rao. Brain tumor magnetic resonance image classification: A deep learning approach. *Soft Computing*, 26(13):6245– 6253, 2022.

[14] D. Liu and et al. 3d large kernel anisotropic network for brain tumour segmentation. In *Proceedings of the International Conference on Neutral Information Processing*, pages 444–454, Cham, Switzerland, 2018. Springer.

[15] Y. Liu, L. Yang, and X. Zhou. Brain tumour detection based on artificial neural networks and a hybrid feature selection method. *IEEE Access*, 5:5820–5830, 2017.

[16] B. H. Menze, A. Jakab, S. Bauer, J. Kalpathy- Cramer, K. Farahani, J. Kirby, Y. Burren, N. Porz, J. Slotboom, and R. Wiest. The multi- modal brain tumour image segmentation benchmark (brats). *IEEE Transactions on Medical Imaging*, 34(10):1993–2024, 2015.

[17] K. Muhammad and et al. Deep learning for multi- grade brain tumour classification in smart healthcare systems: A prospective survey. *IEEE Transactions on Neural Networks and Learning Systems*, 32(2):507–522, 2021.

[18] A. Palkar, C. C. Dias, K. Chadaga, and N. Sam- pathila. Empowering glioma prognosis with trans- parent machine learning and interpretative insights using explainable ai. *IEEE Access*, 12:31697– 31718, 2024.

[19] R. A. Rahman and et al. Advanced ai-driven approach for enhanced brain tumour detection from MRI images utilizing efficientnetb2 with equalization and homomorphic filtering. *BMC Bioinformatics*, 25:2519, 2024.

[20] P. Rajpurkar, E. Chen, O. Banerjee, and E. J. Topol. Ai in health and medicine. *Nature Medicine*, 28(1):31–38, 2022.

[21] R. A. Ramadan and et al. Convolution neural network based automatic localization of landmarks on lateral x-ray images. *Multimedia Tools and Applications*, 2023.

[22] A. Raza, J. Uddin, A. Almuhaimeed, S. Akbar, Q. Zou, and A. Ahmad. Aipssntcn: Predicting anti- inflammatory peptides using fast-text and trans- former encoder-based hybrid word embedding with self-normalized temporal convolutional networks. *Journal of Chemical Information and Modeling*, 63(21):6537–6554, 2023.

[23] A. Rehman, S. Naz, M. I. Razzak, F. Akram, and

M. Imran. A deep learning-based framework for automatic brain tumours classification using transfer learning. *Circuits, Systems, and Signal Processing*, 39(2):757–775, 2020.

[24] A. Raza, J. Uddin, A. Almuhaimeed, S. Akbar,
Q. Zou, and A. Ahmad. Aipssntcn: Predicting anti- inflammatory peptides using fast-text and trans- former encoder-based hybrid word embedding with self-normalized temporal convolutional networks. *Journal of Chemical Information and Modeling*, 63(21):6537–6554, 2023.

[25] A. Rehman, S. Naz, M. I. Razzak, F. Akram, and
M. Imran. A deep learning-based framework for automatic brain tumours classification using transfer learning. *Circuits, Systems, and Signal Processing*, 39(2):757–775, 2020.

S. Solanki, U. P. Singh, S. S. Chouhan, and S. Jain. Brain tumor detection and classification using intelligence techniques: An overview. *IEEE Access*, 11:3482–3500, 2023.

[26] J. Waleed, A. T. Azar, S. Albawi, W. K. Al-Azzawi, I. K. Ibraheem, A. Alkhayyat, I. A. Hameed, and N. A. Kamal. An effective deep learning model to discriminate coronavirus disease from typical pneumonia. *International Journal of Service Science, Management, Engineering, and Technology*, 13(1):1–16, 2023.

[27] H. Yahyaoui, F. Ghazouani, and I. R. Farah. Deep learning guided by an ontology for medical im- ages classification using a multimodal fusion. In *Proceedings of the 2021 International Congress of Advanced Technology and Engineering (ICOTEN)*, pages 1–6, 2021.