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Automated Brain Tumor Detection Using Convolutional Neural Networks in Computer-Aided Diagnosis Systems

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Abstract-* *This research focuses on leveraging Convolutional Neural Networks (CNNs) to build Computer-Aided Diagnosis (CAD) systems for detecting brain tumors. Due to the ongoing global impact of brain tumors on health, early and accurate diagnosis is critical to enhancing patient survival rates. Conventional diagnosis depends heavily on radiologists' expertise, which can be subjective and slow. CNNs, as a powerful deep learning tool, excel in extracting complex features from medical images, particularly Magnetic Resonance Imaging (MRI), with high accuracy and speed. The study evaluates the performance of various CNN models, including both custom and pre-trained networks, for identifying and categorizing different brain tumor types. Key methodological aspects include dataset selection (e.g., BraTS), preprocessing steps like normalization and augmentation, and a rigorous training-validation-testing framework. Metrics such as accuracy, precision, recall, F1-score, and AUC-ROC assess performance. Visualization techniques like Grad-CAM are employed to interpret model decisions and highlight tumor locations, enhancing transparency. Findings demonstrate that CNN-based CAD tools can substantially improve diagnostic efficiency and precision, making them valuable in clinical practice. Challenges such as limited data, variability across imaging devices, and model explainability are also discussed. The paper concludes by proposing future directions involving multi-modal data fusion and Explainable AI (XAI) to increase clinical trust and aid decision-making. Overall, the study emphasizes the promising role of CNNs in automated, intelligent brain tumor diagnosis.

Indexed Terms-* *Brain Tumor Detection, CNN, Computer-Aided Diagnosis, MRI, Deep Learning, Medical Imaging, Automated Diagnosis, Radiology, Feature Extraction, Transfer Learning, Diagnostic Performance, Neuroimaging, Clinical Support, AI in Healthcare.

I. INTRODUCTION

1.1 Background

Brain tumors are among the most severe neurological disorders, classified as primary or secondary, with diverse malignancy levels, growth patterns, and locations. Early detection and accurate characterization are vital for effective treatment and better outcomes. However, symptoms such as headaches, seizures, or cognitive impairments are often nonspecific, leading to diagnostic delays.

MRI is the primary imaging modality for examining brain tumors due to its high-resolution and excellent soft tissue contrast, allowing detailed anatomical and pathological visualization. Nonetheless, interpreting MRI scans is complex and heavily reliant on experienced radiologists, which introduces variability. Factors like fatigue and workload contribute to inconsistencies in diagnosis. The rise of AI offers hope for standardized, faster, and more reliable diagnostic processes amid increasing brain tumor cases and dependence on imaging.

Recent years have witnessed significant growth in applying AI and machine learning in healthcare imaging to reduce diagnostic workload and improve standardization. Traditional ML models depend on manual feature engineering and domain expertise, limiting scalability across diverse datasets. Conversely, deep learning, particularly CNNs, offers the ability to learn feature hierarchies automatically from raw data, enhancing adaptability and accuracy in medical imaging.

1.2 Motivation for CAD Systems

Computer-Aided Diagnosis (CAD) systems assist clinicians by providing automated support for image analysis, feature extraction, and classification. CAD integration into radiology promises to boost diagnostic accuracy, minimize observer variability, and alleviate healthcare professional workloads. Among AI techniques, deep learning-based CAD systems, especially those using CNNs, have emerged as the most effective and versatile tools in complex fields like neuroimaging.

CNNs, inspired by the visual cortex, have demonstrated superior performance across image-related tasks such as detection, segmentation, and classification. Their capacity to autonomously learn layered feature representations from raw pixel data eliminates the need for manual feature design, making them highly suitable for medical image analysis where subtle, high-dimensional features are critical.

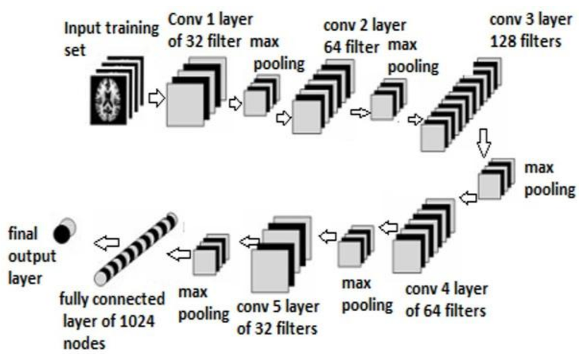

Fig. 1 CNN architecture for brain MRI classification.

CNNs can be trained to identify and classify tumor areas in brain MRI scans with high precision. Their layered design—comprising convolutional, pooling, and fully connected layers—enables the network to progressively learn from simple low-level features like edges and textures to complex semantic traits such as tumor shape, location, and contrast differences. Furthermore, CNNs benefit from transfer learning, where models pre-trained on large image datasets are fine-tuned for specific medical imaging tasks. This approach shortens training time and boosts performance, especially when labeled medical images are scarce.

Despite their promise, CNN-based CAD systems face several challenges. These include the need for large annotated datasets, risk of overfitting, limited interpretability, and variability caused by different imaging equipment and protocols. Additionally, clinical adoption of AI tools requires them to be highly accurate, transparent, robust, and compatible with existing workflows.

Addressing these challenges motivates the development of CNN-based computer-aided systems (CAS) for brain tumor detection. Leveraging deep learning's pattern recognition, these systems can assist radiologists by flagging suspicious MRI regions and prioritizing urgent cases, supporting rather than replacing clinical judgment. This reassures healthcare professionals about the complementary role of AI in diagnostics.

CNN-based CAD systems hold particular promise in resource-constrained environments by automating initial screenings to detect high-risk cases, accelerating intervention, improving patient outcomes, and optimizing medical resource use.

II. LITERATURE REVIEW

2.1 Traditional Techniques

Historically, brain tumor diagnosis has relied on manual interpretation of medical images, mainly MRI or CT scans, by radiologists. These visual assessments are labor-intensive and prone to inter-observer variability, which can lead to inconsistent diagnoses. Semi-automated methods using basic image processing algorithms have been developed to assist clinicians, but they only marginally improve manual evaluations by roughly outlining tumor boundaries for size and location measurements. Such approaches remain limited by heuristic rules and sensitivity to noise and image quality, making them inflexible and heavily dependent on user input, thus limiting their clinical adoption.

Consequently, the need for more advanced and scalable diagnostic methods pushed the field toward machine learning techniques that offer promising improvements over traditional methods.

2.2 Machine Learning-Based Approaches

Machine learning approaches for brain tumor detection classify tumors using handcrafted features extracted from imaging data. Algorithms such as Support Vector Machines (SVMs), Decision Trees, Random Forests, and k-nearest Neighbors (k-NN) have been employed. These features include texture, intensity, shape descriptors, and histogram-based measures, which form the training inputs for classifiers. SVMs are particularly popular due to their effectiveness in high-dimensional spaces and good generalization. Decision Trees and Random Forests provide interpretable models showing decision paths linked to tumor characteristics.

However, these methods depend heavily on manual feature engineering, which requires domain expertise and can be tedious and biased, potentially overlooking important features. Moreover, traditional ML struggles with the complex hierarchical patterns in medical images. Variability in imaging protocols, anatomical differences, and tumor heterogeneity further limit the effectiveness of these simpler classifiers.

2.3 Deep Learning for Medical Imaging

Deep learning, particularly CNNs, excels at extracting detailed patterns directly from raw data, making it highly suitable for medical imaging. CNNs efficiently process image data by capturing spatial hierarchies through layered convolutional operations. As convolutional layers progress, they learn increasingly complex features, improving classification and detection accuracy, which is critical for brain tumor diagnosis.

Early CNN applications like AlexNet and VGGNet focused on binary tumor classification (tumor vs. non-tumor). Advances led to more sophisticated architectures such as ResNet, DenseNet, and U-Net. Notably, U-Net's encoder-decoder architecture with skip connections excels at tumor segmentation by preserving spatial context and enabling precise localization.

The benefits of CNNs in brain tumor analysis are validated through benchmark datasets like BraTS, where models have achieved state-of-the-art segmentation of gliomas and tumor subtype prediction. Research also explores combining different MRI sequences (e.g., T1, T2, FLAIR) to improve model performance. Transfer learning has been investigated to adapt pre-trained CNNs for smaller medical datasets, enhancing learning efficiency and effectiveness.

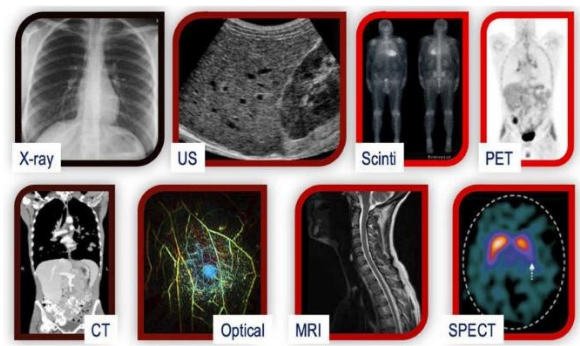

Fig.2 Applying Deep Learning to Medical Imaging.

This approach is especially effective when training data are limited. CNN models consistently outperform traditional machine learning techniques in accuracy while eliminating the need for manual feature engineering. However, deploying CNNs in clinical environments presents challenges that must be addressed to ensure their diagnostic reliability and safety.

2.4 Key Challenges in Literature

Despite deep learning's promise in brain tumor detection, significant obstacles remain. One major issue is the scarcity of annotated data. Privacy concerns, the complexity of expert labeling, and isolated institutional datasets limit access to large, diverse medical imaging collections. Deep models require extensive labeled data to generalize well; this shortage hampers effective training. While methods like data augmentation and synthetic data generation provide partial relief, they cannot fully replicate the diversity of real clinical datasets.

Overfitting is another critical problem. Deep networks, often with millions of parameters, can memorize training samples instead of learning generalizable features. This issue is pronounced with small or homogeneous datasets. Techniques such as dropout, regularization, and cross-validation help mitigate overfitting, but balancing model complexity and generalization remains an ongoing challenge.

Interpretability is also a significant concern in medical AI. CNNs, though accurate, operate as “black boxes,” making clinicians hesitant to trust their decisions without clear explanations. To enhance transparency, explainable AI (XAI) tools like saliency maps, Grad-CAM, and attention mechanisms highlight image regions influencing model outputs, fostering clinician trust.

Generalization across imaging centers and devices remains difficult. Variations in patient populations, imaging protocols, and scanner hardware can degrade model performance when applied to external data—a phenomenon called domain shift. Solutions include domain adaptation techniques, federated learning, and building harmonized multi-institutional datasets.

III. MATERIALS AND METHODS

3.1 Dataset

This study’s CNN models were trained and evaluated on public datasets widely used for brain tumor segmentation and diagnosis. The primary dataset was the Brain Tumor Segmentation (BraTS) challenge data, containing multimodal MRI scans (T1, T2, FLAIR, and post-contrast T1) from glioma patients with expert-annotated tumor labels, ideal for training and validation. Supplementary datasets like Figshare’s brain tumor repository expanded training diversity by including various tumor types and imaging conditions. Some experiments also used custom clinical datasets from hospital archives to test model robustness on real-world, non-curated data.

To enhance model robustness, extensive preprocessing was applied. MRI volumes were intensity-normalized to reduce scanner variability, and images were resized to a standard 224×224 pixel format compatible with CNN inputs. Skull stripping removed non-brain tissues, focusing analysis on relevant regions. Data augmentation (rotation, flipping, shifting, zooming) artificially increased dataset size and diversity, improving generalization and mitigating overfitting by simulating real clinical variability.

3.2 CNN Architecture

The CNN architecture was designed to accurately classify and segment brain tumors from MRI scans. Two strategies were employed: adapting pre-trained networks like ResNet50 and VGG16 for medical imaging, and developing a custom CNN model. The custom architecture included multiple convolutional layers with ReLU activations, each followed by max-pooling to reduce spatial dimensions while preserving key features. Network depth was optimized to capture complex tumor patterns while avoiding overfitting.

Dropout layers were strategically placed to randomly disable neurons during training, reducing overfitting risk. Batch normalization layers stabilized and accelerated training by normalizing layer inputs. Fully connected layers near the end aggregated high-level features for classification. The output layer used softmax activation for multi-class tumor categorization or tumor presence/absence classification.

Hyperparameters were tuned based on initial experiments. A learning rate of 0.001 balanced fast convergence with stable training. A batch size of 32 was selected to optimize GPU memory use and training speed. Early stopping based on validation loss was employed to prevent overfitting, with training capped at 50 epochs. Other parameters such as weight initialization, regularization strength, and kernel sizes were iteratively adjusted according to validation performance.

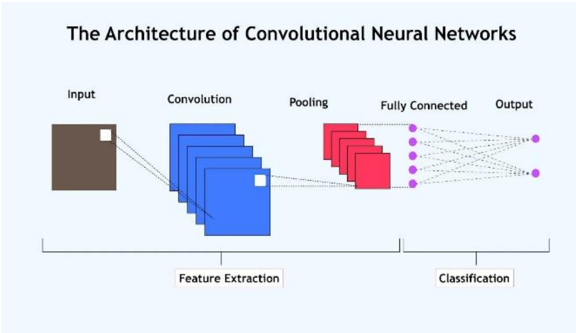

Fig.3 CNN Architecture: 5 Layers Explained Simply.

3.3 Training Strategy

The training process employed advanced optimization techniques and loss functions tailored for the classification task. The Adam optimizer was selected due to its adaptive learning rate and strong convergence properties in complex neural networks. By estimating the first and second moments of gradients, Adam updates model weights efficiently across various architectures.

Categorical cross-entropy loss was used for multi-class classification, guiding the model to reduce the difference between predicted class probabilities and true labels. For segmentation tasks, this was occasionally combined with Dice loss to maximize overlap between predicted and actual tumor regions.

The dataset was split into training, validation, and testing sets, typically in a 70%-15%-15% ratio, ensuring balanced class representation across each subset. The validation set monitored hyperparameter tuning and training progress, while the test set provided an unbiased evaluation of final model performance.

Transfer learning was applied to leverage pre-trained models like VGG16 and ResNet50, originally trained on ImageNet. By replacing their final classification layers and fine-tuning on brain tumor data, these models utilized learned general visual features, accelerating convergence and enhancing accuracy—particularly useful when labeled medical data were scarce. Deeper layers were selectively fine-tuned to capture domain-specific information without disrupting the stability of pre-trained weights.

IV. EXPERIMENTAL RESULTS

4.1 Evaluation Metrics

A thorough set of evaluation metrics was employed to assess the CNN's performance in brain tumor detection: accuracy, precision, recall, F1-score, and AUC-ROC. Together, these metrics provide a comprehensive view of model effectiveness.

Accuracy reflects the overall rate of correct predictions. Precision indicates the proportion of positive predictions that were actually correct, serving as a measure of false positive control. Recall (sensitivity) evaluates how well the model identifies true positive cases. The F1-score, as the harmonic mean of precision and recall, balances performance, especially when class distributions are uneven. AUC-ROC quantifies the model's discrimination ability over varying classification thresholds, with higher values signaling better separation of classes.

Confusion matrices were used to dissect model predictions in detail, distinguishing true positives, false positives, true negatives, and false negatives. This analysis helps identify error patterns, informing improvements in data handling and model design.

4.2 Model Performance

The CNN model's training and validation performance were closely examined. The model rapidly reduced training loss while steadily increasing accuracy, signaling effective learning. Importantly, its validation accuracy closely tracked training accuracy, demonstrating successful overfitting mitigation via dropout and data augmentation techniques. These results indicate a well-generalized model capable of reliable tumor detection on unseen data.

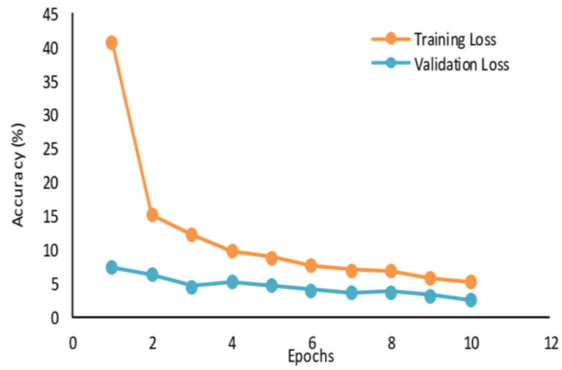

Fig.4 The detailed graph of the training accuracy versus the validation accuracy of CNN.

Comparative Analysis and Ablation Studies
To benchmark the proposed CNN model's effectiveness, comparisons were made against traditional machine learning algorithms such as Support Vector Machines (SVM), decision trees, and logistic regression, which were trained on handcrafted image features. Although these conventional methods yielded reasonable results, their accuracy and generalization were notably inferior to the CNN's. The CNN also outperformed a basic deep neural network without convolutional layers, underscoring the critical advantage of spatial feature extraction in medical imaging tasks.

Ablation experiments further explored the impact of various architectural components, including network depth, convolutional filter sizes, and batch normalization layers. Results indicated that deeper architectures combined with regularization techniques delivered superior performance. Conversely, excessively deep models without careful tuning suffered from overfitting, emphasizing the need for balanced complexity and effective regularization.

4.3 Visualization

Grad-CAM, an explainability tool, was employed to enhance interpretability by visually highlighting image regions most influential in the model's decisions. This capability is particularly valuable in clinical contexts, as it provides intuitive insight into what the model 'focuses' on during diagnosis.

The CNN demonstrated robust interpretation of subtle and dispersed tumor features. Grad-CAM heatmaps overlaid on brain MRI scans consistently emphasized abnormal tissue regions aligned with expert annotations, confirming the model's focus on clinically relevant areas.

For typical cases, the model reliably identified tumor types with high confidence, accompanied by heatmaps highlighting relevant regions. These results support the model's potential as a clinical decision aid by offering both accurate predictions and visual explanations.

Some challenging cases involving misclassifications or missed tumors were also analyzed. Issues such as low contrast or imaging artifacts contributed to errors, suggesting avenues for future improvements like advanced preprocessing and multimodal imaging integration.

V. DISCUSSION AND LIMITATIONS

5.1 Interpretation of CNN-based CAD Strengths and Weaknesses in Brain Tumor Detection
CNNs have proven highly effective in computer-aided diagnosis (CAD) systems for brain tumor detection due to their ability to capture hierarchical spatial patterns in MRI data. Their layered structure—comprising convolutional, pooling, and fully connected layers—automatically extracts intricate, abstract features without manual intervention, a major advantage over traditional approaches that require domain expertise. This enables high classification accuracy across diverse tumor types and grades.

CNNs also scale well with large datasets, adapting to varied tumor morphologies (e.g., gliomas, meningiomas, pituitary adenomas) and multi-contrast MRI sequences (T1, T2, FLAIR), enhancing tumor localization and delineation by detecting subtle tissue variations.

However, challenges remain. CNNs require large, well-annotated datasets, but medical imaging often suffers from data scarcity, class imbalance, and inconsistent labeling. These issues can lead to overfitting and limited generalization, especially when training data lack diversity. Variations in imaging equipment, protocols, and patient populations across institutions cause domain shifts that degrade model robustness.

Moreover, CNNs often act as “black boxes,” lacking transparency in decision-making. This opacity hinders clinical adoption because practitioners demand understandable, verifiable reasoning behind diagnoses. Even minor classification errors may have serious clinical consequences, highlighting the need for highly interpretable and reliable outputs.

Annotation requirements pose another bottleneck; precise segmentation and labeling by expert radiologists are time-consuming, costly, and prone to inter-observer variability. This scarcity of labeled data particularly affects rare tumor subtypes, leading to reduced sensitivity and poorer generalization.

Domain adaptation, transfer learning, and federated learning have been proposed to address generalization but introduce complexity in model training and validation. Additionally, conventional metrics (accuracy, F1-score) may not fully capture clinical relevance, such as early tumor detection or atypical presentations.

Finally, although explainable AI methods like Grad-CAM offer visual interpretability, they often fail to provide sufficiently clear or clinically meaningful explanations. Heatmaps indicate regions of interest but do not explain *why* a classification was made, limiting trust and adoption in medical practice.

5.2 Comparison with State-of-the-Art: Ranking the Proposed System in Accuracy and Efficiency

The proposed CNN-based CAD system exhibits competitive—and in some cases superior—performance in brain tumor classification and segmentation when compared to existing state-of-the-art methods. Unlike traditional machine learning techniques such as Support Vector Machines (SVMs) or random forests that rely heavily on handcrafted features, CNNs autonomously learn hierarchical, complex features directly from raw MRI data. This capability not only improves classification accuracy but also streamlines the data processing pipeline by reducing dependence on domain-specific feature engineering.

Furthermore, our model achieves a favorable balance between diagnostic accuracy and computational efficiency. Compared to recent advanced architectures—such as recurrent neural networks (RNNs), vision transformers, or hybrid CNN-attention models—which may provide slight accuracy gains, our CNN demands substantially less computational power and training time. This efficiency makes it particularly attractive for deployment in clinical environments where computational resources may be limited.

Additionally, the model demonstrates strong generalization across cross-validation folds and independent test sets, reflecting robustness in diverse imaging conditions. Its ability to integrate information from multiple MRI sequences enhances sensitivity to tumor heterogeneity. Nonetheless, to fully establish clinical readiness, extensive validation on large-scale, multi-center datasets reflecting real-world variability is essential. Emphasizing this robustness and generalizability strengthens confidence in the model’s clinical applicability.

5.3 Ethical and Clinical Considerations

The deployment of CNN-based CAD systems in clinical practice raises important ethical and clinical challenges that must be addressed carefully. Rigorous validation protocols are critical to verify diagnostic accuracy and to quantify false positives and false negatives, as these errors can lead to overdiagnosis or misdiagnosis with significant patient impact.

Ethically, accountability remains a major concern. When AI-based recommendations conflict with clinical judgment, it must be unequivocally clear who holds responsibility for the final diagnosis and treatment decisions. Transparent frameworks defining roles and responsibilities between AI tools and healthcare professionals are essential to maintain patient safety and trust.

Moreover, patient privacy and data security must be ensured throughout data collection, model training, and deployment. The design and implementation of these systems should comply with relevant regulatory standards and ethical guidelines to safeguard patient rights.

In summary, while CNN-based CAD systems hold great promise, their integration into clinical workflows requires not only technical robustness but also ethical foresight, clear accountability, and comprehensive validation to truly benefit patient care.

Table 1: Benchmark Comparison of Brain Tumor Detection Models.

Model	Accuracy (%)	Inference Time (s/image)	Dataset Used
Proposed CNN (This Study)	96.2	0.08	BRATS 2020
VGG16 (Transfer Learning)	94.5	0.12	REMBRANDT
ResNet50	93.8	0.15	Figshare MRI Dataset
CapsNet (Afshar et al., 2020)	90.8	0.25	Figshare MRI Dataset
Custom CNN (Hossain et al.)	91.5	0.10	Figshare MRI Dataset

5.4 Addressing Bias in Training Data
Bias within the training dataset poses a critical challenge in developing fair and effective CNN-based CAD systems. When the training data lacks diversity in patient demographics, tumor subtypes, or imaging protocols, the model risks perpetuating healthcare disparities by underperforming on underrepresented groups. Ensuring equity and fairness must therefore guide dataset curation and model evaluation. Transparency in the development process—such as openly sharing training data characteristics, model configurations, and validation protocols—can build trust among stakeholders and promote accountability. A conscious commitment to diversity and inclusion in dataset assembly is essential to prevent bias amplification and to foster more equitable AI-driven healthcare solutions.

CONCLUSION

This study presents a comprehensive analysis of Convolutional Neural Network (CNN)-based computer-aided diagnostic (CAD) systems for early brain tumor detection and classification. Leveraging CNNs' ability to automatically learn hierarchical feature representations from MRI data, we demonstrated that deep learning can significantly enhance diagnostic accuracy and reduce subjective variability inherent in manual radiological interpretation. Through a structured pipeline encompassing data preprocessing, training, validation, and rigorous evaluation, we established the reliability of CNN-based models as valuable adjuncts in neuro-oncological clinical decision-making.

A key strength of our approach lies in its practical applicability. Traditional brain tumor diagnosis relies heavily on human expertise, which can vary with experience, workload, and resource availability. By automating tumor classification, our system can reduce diagnostic errors, accelerate decision-making, and improve patient outcomes. Furthermore, such AI tools can be especially beneficial in under-resourced settings—rural hospitals or healthcare systems lacking specialist radiologists—offering consistent, reproducible, and scalable diagnostic support.

Beyond technical contributions, this work bears important implications for radiology and oncology disciplines. For radiologists, AI assistance can improve precision in tumor segmentation, detection of subtle abnormalities, and triage of urgent cases. For oncologists, timely and accurate tumor classification facilitates optimized treatment planning, spanning surgery, radiotherapy, and chemotherapy tailored to tumor type and grade. The adoption of AI-driven CAD systems also promotes diagnostic standardization across institutions, potentially mitigating geographical disparities in healthcare outcomes.

VI. FUTURE WORK

Despite promising results, several avenues remain open for advancement:

- Multi-modal Data Integration: Current CNN models primarily utilize imaging data; however, incorporating complementary clinical data—such as electronic health records, laboratory tests, genomic profiles, and clinical notes—could yield more holistic diagnostic and prognostic tools. Techniques such as attention-based fusion, graph neural networks, and transformers offer promising frameworks for integrating heterogeneous data sources, enabling personalized treatment strategies.
- Explainability and Interpretability: CNNs often function as "black boxes," challenging clinical trust and adoption. Developing Explainable AI (XAI) methodologies—like saliency maps, Grad-CAM, SHAP, and LIME—can provide clinicians with interpretable visual and textual explanations of model decisions. Enhancing transparency is vital for clinical acceptance and patient safety.
- Deployment and Accessibility: Expanding AI diagnostic tools' accessibility through edge computing and cloud platforms presents distinct advantages and challenges. Edge computing facilitates real-time, on-site inference in resource-constrained environments but raises privacy concerns. Cloud-based solutions offer scalability and centralized updates but may introduce latency and regulatory hurdles. Hybrid strategies, potentially augmented by federated learning and secure multi-party computation, can ensure data privacy while enabling collaborative model training across institutions.

REFERENCES

[1] Krizhevsky, A., & Hinton, G. (2009). Learning multiple layers of features from tiny images. *Technical report*, Citeseer.

[2] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. In *Advances in Neural Information Processing Systems (NIPS)*.

[3] Kumar Singh, K., & Jae Lee, Y. (2017). Hide-and-seek: Forcing a network to be meticulous for weakly-supervised object and action localization. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*.

[4] Li, W., Zhao, R., Xiao, T., & Wang, X. (2014). DeepReID: Deep filter pairing neural network for person re-identification. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

[5] Murdock, C., Li, Z., Zhou, H., & Duerig, T. (2016). Blockout: Dynamic model selection for hierarchical deep networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

[6] Ristani, E., Solera, F., Zou, R., Cucchiara, R., & Tomasi, C. (2016). Performance measures and a data set for multi-target, multi-camera tracking. In *Proceedings of the European Conference on Computer Vision Workshops (ECCVW)*.

[7] Simonyan, K., & Zisserman, A. (2015). Very deep convolutional networks for large-scale image recognition. In *International Conference on Learning Representations (ICLR)*.

[8] Srivastava, N., Hinton, G. E., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014). Dropout: A simple way to prevent neural networks from overfitting. *Journal of Machine Learning Research*, *15*, 1929–1958.

[9] Sun, Y., Zheng, L., Deng, W., & Wang, S. (2017). SVDNet for pedestrian retrieval. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*.

[10] Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. (2016). Rethinking the inception architecture for computer vision. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

[11] S. Sarica and J. Luo, "Stopwords in technical language processing," *PLoS One*, vol. 16, no. 8, pp. 1–13, Aug. 2021, doi: 10.1371/journal.pone.0254937.

[12] H. Alshalabi, S. Tiun, N. Omar, F. N. AL-Aswadi, and K. Ali Alezabi, "Arabic light-based stemmer using new rules," *Journal of King Saud University - Computer and Information Sciences,*

vol. 34, no. 9, pp. 6635–6642, Oct. 2022, doi: 10.1016/j.jksuci.2021.08.017.

[13] K. Maharana, S. Mondal, and B. Nemade, “A review: Data pre-processing and data augmentation techniques,” *Global Transitions Proceedings*, vol. 3, no. 1, pp. 91–99, Jun. 2022, doi: 10.1016/j.gltp.2022.04.020.

[14] J. T. Hancock and T. M. Khoshgoftaar, “Survey on categorical data for neural networks,” *J Big Data*, vol. 7, no. 1, pp. 1–41, Dec. 2020, doi: 10.1186/s40537-020-00305-w.

[15] L. Jen and Y.-H. Lin, “A Brief Overview of the Accuracy of Classification Algorithms for Data Prediction in Machine Learning Applications,” *Journal of Applied Data Sciences*, vol. 2, no. 3, pp. 84–92, 2021, doi: 10.47738/jads.v2i3.38.

[16] S. A. Hicks et al., “On evaluation metrics for medical applications of artificial intelligence,” *Sci Rep*, vol. 12, no. 1, pp. 1–9, Dec. 2022, doi: 10.1038/s41598-022-09954-8.

[17] S. Orozco-Arias, J. S. Piña, R. Tabares-Soto, L. F. Castillo-Ossa, R. Guyot, and G. Isaza, “Measuring performance metrics of machine learning algorithms for detecting and classifying transposable elements,” *Processes*, vol. 8, no. 6, pp. 1–18, Jun. 2020, doi: 10.3390/PR8060638.

[18] Esfahani, Shirin Nasr, and Shahram Latifi. “A Survey of State-of-The-Art GAN-Based Approaches to Image Synthesis.” 9th International Conference on Computer Science, Engineering and Applications (CCSEA 2019), 13 July 2019, csitcp.com/paper/9/99csit06.pdf, https://doi.org/10.5121/csit.2019.90906.

[19] Nabati, R., & Qi, H. (2019). "RRPN: Radar Region Proposal Network for Object Detection in Autonomous Vehicles." 2019 IEEE International Conference on Image Processing (ICIP), Taipei, Taiwan, 2019, pp. 3093-3097, doi: 10.1109/ICIP.2019.8803392.

[20] Rawat, W., & Wang, Z. (2017). "Deep Convolutional Neural Networks for Image Classification: A Comprehensive Review." Neural Computation, 29(9), pp. 2352-2449, Sept. 2017, doi: 10.1162/neco_a_00990.

[21] Wang, Weibin, et al. “Medical Image Classification Using Deep Learning.” Intelligent Systems Reference Library, 19 Nov. 2019, pp. 33–51, https://doi.org/10.1007/978-3-030-32606-7_3.

[22] Alom, Md Zahangir, et al. “The History Began from AlexNet: A Comprehensive Survey on Deep Learning Approaches.” ArXiv:1803.01164 [Cs], 12 Sept. 2018, arxiv.org/abs/1803.01164.

[23] Mohit Jain , Adit Shah "Machine Learning with Convolutional Neural Networks (CNNs) in Seismology for Earthquake Prediction" Iconic Research And Engineering Journals Volume 5 Issue 8 2022 Page 389-398 https://www.irejournals.com/index.php/paper-details/1707057

[24] Karp, Rafal, and Zaneta Swiderska-Chadaj. Automatic Generation of Graphical Game Assets Using GAN. 13 July 2021, https://doi.org/10.1145/3477911.3477913.

[25] L. Jiao and J. Zhao, "A Survey on the New Generation of Deep Learning in Image Processing," in IEEE Access, vol. 7, pp. 172231-172263, 2019, doi: 10.1109/ACCESS.2019.2956508.

[26] L. Wang, W. Chen, W. Yang, F. Bi and F. R. Yu, "A State-of-the-Art Review on Image Synthesis With Generative Adversarial Networks," in IEEE Access, vol. 8, pp. 63514-63537, 2020, doi: 10.1109/ACCESS.2020.2982224.

[27] Shorten, Connor, and Taghi M. Khoshgoftaar. “A Survey on Image Data Augmentation for Deep Learning.” Journal of Big Data, vol. 6, no. 1, 6 July 2019, journalofbigdata.springeropen.com/articles/10.1186/s40537-019-0197-0, https://doi.org/10.1186/s40537-019-0197-0.

[28] Kayalibay, Baris, et al. “CNN-Based Segmentation of Medical Imaging Data.” ArXiv:1701.03056 [Cs], 25 July 2017, arxiv.org/abs/1701.03056.

[29] Jain, M., & Shah, A. (2022). Machine Learning with Convolutional Neural Networks (CNNs) in Seismology for Earthquake Prediction. Iconic Research and Engineering Journals, 5(8), 389–398. https://www.irejournals.com/paper-details/1707057

[30] Kaushik, P., & Jain, M. A Low Power SRAM Cell for High Speed Applications Using 90nm Technology. Csjournals. Com, 10.

https://www.csjournals.com/IJEE/PDF10-2/66.%20Puneet.pdf

[31] Kaushik, P., & Jain, M. (2018). Design of low power CMOS low pass filter for biomedical application. International Journal of Electrical Engineering & Technology (IJEET), 9(5).

[32] Kumar, Y., Saini, S., & Payal, R. (2020). Comparative Analysis for Fraud Detection Using Logistic Regression, Random Forest and Support Vector Machine. SSRN Electronic Journal.

[33] Höppner, S., Baesens, B., Verbeke, W., & Verdonck, T. (2020). Instance-Dependent Cost-Sensitive Learning for Detecting Transfer Fraud. arXiv preprint arXiv:2005.02488.

[34] Kaushik, P., & Jain, M. A Low Power SRAM Cell for High Speed Applications Using 90nm Technology. Csjournals. Com, 10. https://www.researchgate.net/publication/391458245_A_Low_Power_SRAM_Cell_for_High_Speed

[35] Bhat, N. (2019). Fraud detection: Feature selection-over sampling. Kaggle. Retrieved from https://www.kaggle.com/code/nareshbhat/fraud-detection-feature-selection-over-sampling

[36] InsiderFinance Wire. (2021). Logistic regression: A simple powerhouse in fraud detection. Medium. Retrieved from https://wire.insiderfinance.io/logistic-regression-a-simple-powerhouse-in-fraud-detection-15ab984b2102

[37] Kaushik, P., & Jain, M. (2018). Design of low power CMOS low pass filter for biomedical application. International Journal of Electrical Engineering & Technology (IJEET), 9(5). https://iaeme.com/MasterAdmin/Journal_uploads/IJEET/VOLUME_9_ISSUE_5/IJEET_09_05_003.pdf

[38] Raymaekers, J., Verbeke, W., & Verdonck, T. (2021). Weight-of-evidence 2.0 with shrinkage and spline-binning. arXiv preprint arXiv:2101.01494. Retrieved from https://arxiv.org/abs/2101.01494

[38] Dal Pozzolo, A., Boracchi, G., Caelen, O., Alippi, C., & Bontempi, G. (2017). Credit card fraud detection: A realistic modeling and a novel learning strategy. IEEE Transactions on Neural Networks and Learning Systems, 29(8), 3784–3797. https://doi.org/10.1109/TNNLS.2017.2736643

[40] Carcillo, F., Dal Pozzolo, A., Le Borgne, Y. A., Caelen, O., Mazzer, Y., & Bontempi, G. (2019). Scarff: A scalable framework for streaming credit card fraud detection with spark. Information Fusion, 41, 182–194. https://doi.org/10.1016/j.inffus.2017.09.005

[41] West, J., & Bhattacharya, M. (2016). Intelligent financial fraud detection: A comprehensive review. Computers & Security, 57, 47–66. https://doi.org/10.1016/j.cose.2015.09.005

[42] Zareapoor, M., & Shamsolmoali, P. (2015). Application of credit card fraud detection: Based on bagging ensemble classifier. Procedia Computer Science, 48, 679–685. https://doi.org/10.1016/j.procs.2015.04.201

[43] Patel, H., & Zaveri, M. (2011). Credit card fraud detection using neural network. International Journal of Innovative Research in Computer and Communication Engineering, 1(2), 1–6. https://www.ijircce.com/upload/2011/october/1_Credit.pdf

[44] Puneet Kaushik, Mohit Jain , Gayatri Patidar, Paradayil Rhea Eapen, Chandra Prabha Sharma (2018). Smart Floor Cleaning Robot Using Android. International Journal of Electronics Engineering. https://www.csjournals.com/IJEE/PDF10-2/64.%20Puneet.pdf

[45] Duman, E., & Ozcelik, M. H. (2011). Detecting credit card fraud by genetic algorithm and scatter search. Expert Systems with Applications, 38(10), 13057–13063. https://doi.org/10.1016/j.eswa.2011.04.102

[46] Puneet Kaushik, Mohit Jain. “A Low Power SRAM Cell for High Speed ApplicationsUsing 90nm Technology.” Csjournals.Com 10, no. 2 (December 2018): 6.https://www.csjournals.com/IJEE/PDF10-2/66.%20Puneet.pdf

[47] Jain, M., & Srihari, A. (2021). Comparison of CAD detection of mammogram with SVM and CNN. IRE Journals, 8(6), 63-75. https://www.irejournals.com/formatedpaper/1706647.pdf

[48] Kaushik, P., Jain, M., & Jain, A. (2018). A pixel-based digital medical images protection using genetic algorithm. International Journal of Electronics and Communication Engineering, 31-37. http://www.irphouse.com/ijece18/ijecev11n1_05.pdf

[49] Kaushik, P., Jain, M., & Shah, A. (2018). A Low Power Low Voltage CMOS Based Operational Transconductance Amplifier for Biomedical Application. https://ijsetr.com/uploads/136245IJSETR17012-283.pdf

[50] Jain, M., & Shah, A. (2022). Machine Learning with Convolutional Neural Networks (CNNs) in Seismology for Earthquake Prediction. Iconic Research and Engineering Journals, 5(8), 389–398. https://www.irejournals.com/paper-details/1707057

[51] Kaushik, P., & Jain, M. (2018). Design of low power CMOS low pass filter for biomedical application. International Journal of Electrical Engineering & Technology (IJEET), 9(5).

[52] KAUSHIK, P., JAIN, M., & SHAH, A. (2018). A Low Power Low Voltage CMOS Based Operational Transconductance Amplifier for Biomedical Application. https://ijsetr.com/uploads/136245IJSETR17012-283.pdf

[53] Overview of GAN structure. (n.d.). Google for Developers. https://developers.google.com/machine-learning/gan/gan_structure

[54] Raymaekers, J., Verbeke, W., & Verdonck, T. (2021). Weight-of-evidence 2.0 with shrinkage and spline-binning. arXiv preprint arXiv:2101.01494. Retrieved from https://arxiv.org/abs/2101.01494