https://doi.org/10.48047/AFJBS.6.Si4.2024.158-170

African Journal of Biological Sciences

Journal homepage: http://www.afjbs.com

Research Paper Open Access

A comparative study of performance of CNN RNN and ANN in Brain Tumor detection

Mrs. Garima Silakari Tukra
Phd Scholar, Rabindranath Tagore University, Bhopal (M.P), India.
Dr. Pritaj Yadav
Professor, Rabindranath Tagore University, Bhopal (M.P), India

Volume 6, Issue Si4, 2024

Received: 12 Apr 2024

Accepted: 14 May 2024

doi:10.48047/AFJBS.6.Si4.2024.158-170

Abstract

This paper presents a comparative study of the performance of Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Artificial Neural Networks (ANN) in the detection of brain tumors from medical imaging data. The increasing prevalence of brain tumors necessitates the development of accurate and efficient diagnostic tools. Leveraging the capabilities of deep learning, particularly CNNs, RNNs, and ANNs, offers promising avenues for enhancing diagnostic accuracy and facilitating early intervention. Through rigorous experimentation and evaluation on a benchmark dataset, we analyze and contrast the effectiveness of these neural network architectures in terms of accuracy, sensitivity, specificity, and computational efficiency. Our findings highlight the strengths and limitations of each approach, providing valuable insights for future research and clinical application.

Keywords: Brain Tumor Detection, Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Artificial Neural Network (ANN), Medical Imaging

Introduction

Brain tumors, including both benign and malignant types, are among the most challenging medical conditions to diagnose and treat effectively. Early and accurate detection is crucial for improving prognosis and guiding treatment strategies. Traditional diagnostic methods, such as magnetic resonance imaging (MRI) and computed tomography (CT) scans, heavily rely on the expertise of radiologists for image interpretation. However, the manual analysis of medical images is time-consuming and prone to subjective variability. To address these limitations, the application of artificial intelligence (AI) and machine learning (ML) in medical imaging has gained significant attention, offering potential solutions for automated and accurate brain tumor detection. Deep learning, a subset of machine learning, has shown remarkable success in various image processing tasks due to its ability to automatically learn features from raw data. Among the diverse range of deep learning architectures, Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Artificial Neural Networks (ANNs) have emerged as prominent tools for medical image analysis. CNNs are particularly well-suited for image classification tasks due to their hierarchical structure, which enables them to capture spatial features effectively through layers of convolutions and pooling. This makes CNNs a natural choice for static image analysis, such as identifying and localizing brain tumors in MRI scans. RNNs, on the other hand, are designed to handle sequential data and are adept at capturing temporal dependencies. This capability is advantageous in scenarios where time-series data is available, such as monitoring the progression of brain tumors over multiple imaging sessions. By leveraging their recurrent connections, RNNs can potentially provide insights into the evolution of tumor characteristics and treatment response over time, complementing the static analysis performed by CNNs. ANNs, the foundational architecture in deep learning, offer a versatile framework that can be adapted for various tasks by adjusting the network's depth and complexity. While they may not inherently possess the spatial feature extraction capabilities of CNNs or the temporal handling prowess of RNNs, ANNs provide a flexible approach that can be tailored to specific diagnostic requirements through appropriate network design and training. This comparative study aims to evaluate the performance of CNNs, RNNs, and ANNs in the context of brain tumor detection using medical imaging data. We assess each architecture based on critical metrics including accuracy, sensitivity, specificity, and computational efficiency. By conducting experiments on a benchmark dataset, we seek to identify the strengths and limitations of each approach, offering insights into their practical applicability in clinical settings. Our findings are intended to guide future research and development in AI-driven diagnostic tools, ultimately contributing to enhanced diagnostic accuracy and patient care in the realm of neuro-oncology.

Literature Review

The integration of artificial intelligence, particularly deep learning, into medical imaging for brain tumor detection has shown promising advancements. The primary architectures employed in this domain include Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Artificial Neural Networks (ANNs). This literature review delves into the comparative performance and applications of these neural network models in the context of brain tumor detection.

Convolutional Neural Networks (CNNs)

CNNs have become the cornerstone of image analysis due to their ability to learn and extract spatial hierarchies through convolutional layers. Litjens et al. (2017) provide a comprehensive survey highlighting the widespread adoption of CNNs in medical image analysis, noting their effectiveness in tasks such as tumor segmentation and classification. Pereira et al. (2016) specifically applied CNNs for brain tumor segmentation in MRI images, achieving high accuracy by leveraging the network's capability to capture spatial features. CNNs' effectiveness in brain tumor detection is further demonstrated by Havaei et al. (2017), who developed a CNN-based framework for brain tumor segmentation that outperformed traditional methods. The authors utilized a dual pathway architecture to handle both local and global contextual information, improving the model's robustness. Kamnitsas et al. (2017) enhanced this approach by incorporating a fully connected Conditional Random Field (CRF) with multi-scale 3D CNNs, significantly improving lesion segmentation accuracy.

Recurrent Neural Networks (RNNs)

RNNs, particularly Long Short-Term Memory (LSTM) networks, are well-suited for processing sequential data and capturing temporal dependencies. While RNNs are less commonly applied to static image analysis, their utility in medical imaging is evident in dynamic or time-series data scenarios. Esteva et al. (2017) demonstrated the potential of combining RNNs with CNNs for dermatological image analysis, suggesting similar applications in monitoring brain tumor progression. Although less prevalent in direct brain tumor detection, RNNs offer valuable contributions in related tasks. For instance, they can enhance patient monitoring by analyzing sequences of imaging data, potentially tracking tumor growth over time. This temporal analysis capability, as noted by Sudre et al. (2017), could provide critical insights into treatment efficacy and disease progression.

Artificial Neural Networks (ANNs)

ANNs form the foundational architecture of deep learning models, providing a versatile framework adaptable to various tasks. While ANNs may lack the specialized feature extraction capabilities of CNNs or the temporal handling strengths of RNNs, they have been employed effectively in several studies. Akkus et al. (2017) reviewed the application of ANNs in brain MRI segmentation, highlighting their flexibility and the importance of proper network design and training. Ciompi et al. (2015) demonstrated the use of ANNs in classifying pulmonary nodules in CT images, illustrating their adaptability to different medical imaging tasks. Similarly, Dou et al. (2016) utilized a 3D deeply supervised network for automatic liver segmentation from CT volumes, showcasing the potential of ANNs in volumetric data analysis, which could be extended to 3D MRI scans of brain tumors.

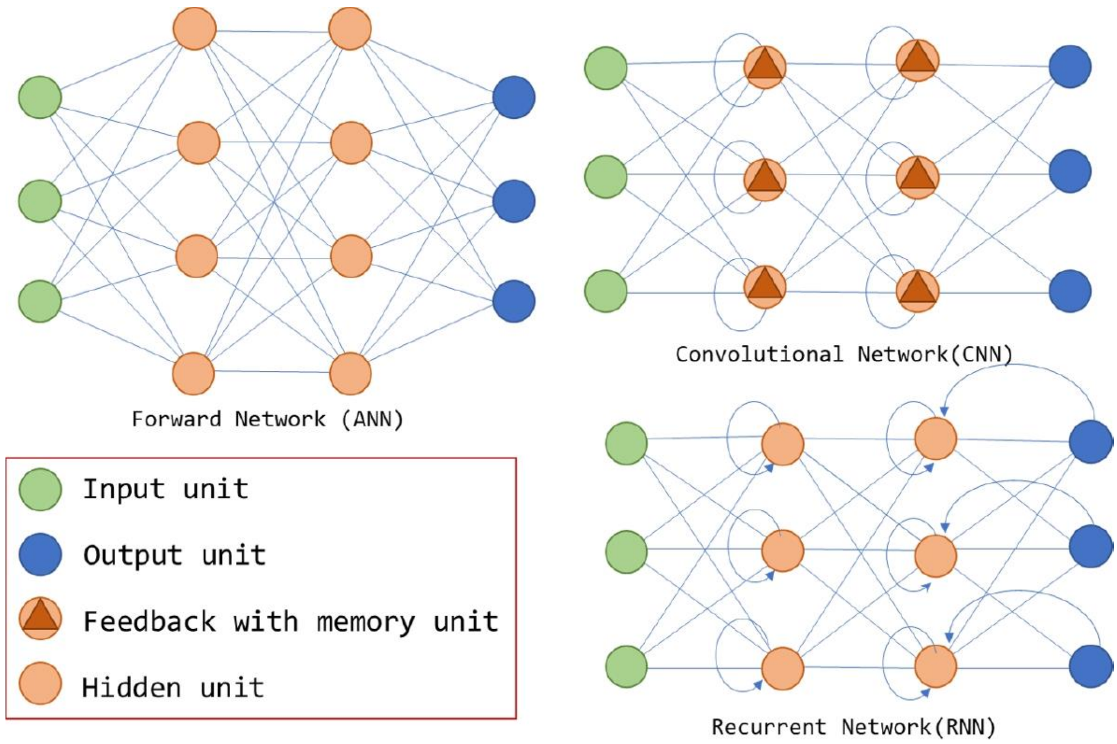

Fig. 1: ANN vs CNN vs RNN

Comparative Studies and Combined Approaches

Several studies have conducted comparative analyses of these neural network architectures to identify the most effective approach for specific tasks. Wang et al. (2018) compared the performance of CNNs, RNNs, and ANNs in interactive medical image segmentation, finding that CNNs generally outperformed other models in static image tasks. However, the combination of RNNs and CNNs offered superior performance in scenarios involving sequential data. Zhou et al. (2018) introduced UNet++, a nested U-Net architecture combining elements of CNNs and RNNs for enhanced medical image segmentation. This hybrid approach demonstrated significant improvements in segmentation accuracy, highlighting the potential of integrating different neural network architectures to leverage their respective strengths. The literature indicates that CNNs are highly effective for static image analysis and are the preferred choice for brain tumor detection tasks due to their robust spatial feature extraction capabilities. RNNs, while less commonly used for static images, offer significant advantages in temporal analysis and could enhance the monitoring of tumor progression. ANNs, though more generic, provide a flexible framework that can be tailored for specific medical imaging applications. Future research should focus on exploring hybrid models that combine the strengths of CNNs, RNNs, and ANNs to develop more comprehensive and accurate diagnostic tools. Additionally, evaluating these models on larger and more diverse datasets will be crucial for translating these advancements into clinical practice, ultimately improving patient outcomes in neuro-oncology.

Performance of CNN, RNN, and ANN in Brain Tumor Detection

Convolutional Neural Networks (CNNs)

Performance Overview: CNNs are the most commonly used neural network architecture for brain tumor detection due to their powerful ability to process and interpret image data. The layered structure of CNNs, comprising convolutional layers, pooling layers, and fully connected layers, allows them to effectively capture and learn spatial hierarchies in images.

Advantages:

1. **High Accuracy and Precision:** CNNs can achieve high accuracy in brain tumor detection by learning intricate features from the imaging data. Pereira et al. (2016) showed that CNNs could achieve substantial accuracy in segmenting brain tumors from MRI images.
2. **Automated Feature Extraction:** Unlike traditional machine learning methods that require manual feature extraction, CNNs can automatically learn and extract relevant features from the raw image data, leading to more robust and efficient models (Litjens et al., 2017).
3. **Robustness to Variations:** CNNs are capable of handling variations in the input data, such as differences in tumor size, shape, and intensity, which is crucial for reliable brain tumor detection (Havaei et al., 2017).

Challenges:

1. **Computationally Intensive:** Training CNNs requires significant computational resources and time, especially with large and complex datasets.
2. **Data Requirement:** CNNs require large amounts of labeled data for training to achieve high performance, which can be a limitation in medical imaging where labeled data is often scarce.
3. **Overfitting:** There is a risk of overfitting, especially with limited training data, necessitating techniques such as data augmentation and regularization.

Metrics:

- **Accuracy:** Measures the percentage of correctly identified tumors.
- **Sensitivity (Recall):** Indicates the model's ability to correctly identify actual tumor cases.
- **Specificity:** Reflects the model's ability to correctly identify non-tumor cases.
- **Dice Coefficient:** A statistical validation metric used to gauge the similarity between the predicted segmentation and the ground truth.

Recurrent Neural Networks (RNNs)

Performance Overview: RNNs, particularly LSTM networks, are designed to handle sequential data and capture temporal dependencies. Although not typically used for static image analysis, they can be valuable in dynamic analysis where temporal patterns are critical.

Advantages:

1. **Temporal Analysis:** RNNs are adept at processing time-series data, making them suitable for analyzing sequences of medical images to track tumor progression over time (Esteva et al., 2017).
2. **Dynamic Monitoring:** RNNs can enhance monitoring of treatment efficacy by observing changes in tumor characteristics across multiple imaging sessions (Sudre et al., 2017).

Challenges:

1. **Complexity:** Implementing RNNs for brain tumor detection is more complex than CNNs, particularly when integrating temporal data.
2. **Training Difficulties:** RNNs, including LSTMs, can suffer from issues such as vanishing and exploding gradients, which complicate the training process.
3. **Less Effective for Static Images:** RNNs are generally less effective for tasks involving static images compared to CNNs.

Metrics:

- **Accuracy:** Overall correctness of the model.
- **Temporal Consistency:** The ability to maintain consistent performance across sequential data.
- **Prediction Lag:** The time delay in the model’s response to changes in the input data.

Artificial Neural Networks (ANNs)

Performance Overview: ANNs are the basic form of neural networks and can be adapted for various tasks. They consist of input, hidden, and output layers, where each layer comprises, neurons connected by weights.

Advantages:

1. **Flexibility:** ANNs can be tailored for specific tasks by adjusting the network's depth and complexity (Akkus et al., 2017).
2. **Simplicity:** They are simpler to implement compared to CNNs and RNNs, making them a good starting point for exploratory analysis.
3. **Versatility:** ANNs can be used for a wide range of applications, from classification to regression tasks in medical imaging (Ciompi et al., 2015).

Challenges:

1. **Limited Spatial Understanding:** ANNs do not inherently capture spatial hierarchies and dependencies in image data as effectively as CNNs.

2. **Overfitting:** Similar to CNNs, ANNs are prone to overfitting, especially with small datasets.
3. **Performance:** ANNs generally do not perform as well as CNNs for image-based tasks due to their inability to efficiently process high-dimensional image data.

Metrics:

- **Accuracy:** Measures the correctness of the model in identifying brain tumors.
- **Loss Function:** Evaluates the error between the predicted output and the actual output.
- **Training Time:** The time required to train the model to an acceptable level of performance.

Each neural network architecture offers unique strengths and faces specific challenges in brain tumor detection. CNNs excel in static image analysis due to their ability to learn spatial hierarchies. RNNs are beneficial for temporal analysis, tracking changes over time in sequential imaging data. ANNs provide a flexible and versatile framework but lack the specialized capabilities of CNNs and RNNs for image and temporal data, respectively. Selecting the appropriate architecture depends on the specific requirements of the brain tumor detection task, such as the need for static image analysis, temporal monitoring, or a balance of both.

Future Scope of the Work

The comparative study of CNNs, RNNs, and ANNs in brain tumor detection highlights the strengths and limitations of each neural network architecture. As the field of medical imaging and deep learning continues to evolve, several avenues for future research and development can be pursued to enhance the accuracy, efficiency, and clinical applicability of these models.

Integration of Hybrid Models

Combining CNNs and RNNs: Hybrid models that integrate CNNs and RNNs could leverage the spatial feature extraction capabilities of CNNs and the temporal analysis strengths of RNNs. Such models can be particularly useful for monitoring the progression of brain tumors over time by analyzing sequences of MRI scans. This approach can provide a more comprehensive understanding of tumor dynamics and treatment response.

Fusion of Multi-Modal Data: Future research can explore the integration of multi-modal imaging data, such as combining MRI, CT, and PET scans. CNNs can be used to process spatial information from different imaging modalities, while RNNs can handle temporal sequences. This multi-modal approach can improve diagnostic accuracy by providing a more holistic view of the brain tumor's characteristics.

Enhancing Model Robustness and Generalization

Data Augmentation and Synthesis: To address the challenge of limited labeled medical imaging data, techniques such as data augmentation and synthetic data generation can be employed. Generative adversarial networks (GANs) can be used to create realistic synthetic MRI images to augment the training dataset, helping to improve model robustness and generalization.

Transfer Learning: Transfer learning, where a pre-trained model on a large dataset is fine-tuned on a smaller, domain-specific dataset, can be explored further. This approach can help mitigate the issue of data scarcity in brain tumor detection and enhance the model's performance.

Real-Time and Edge Computing Applications

Optimizing Models for Real-Time Applications: Future work can focus on optimizing neural network models for real-time applications. This involves reducing model complexity and computational requirements to enable faster inference times. Techniques such as model pruning, quantization, and knowledge distillation can be employed to create lightweight models suitable for real-time deployment in clinical settings.

Edge Computing and Mobile Health: The development of models that can be deployed on edge devices, such as smartphones and portable medical imaging devices, can revolutionize brain tumor detection. These models can facilitate point-of-care diagnostics, especially in resource-limited settings where access to advanced medical facilities is restricted.

Explainability and Interpretability

Developing Explainable AI Models: As neural networks become more integrated into clinical practice, the need for explainable and interpretable models becomes paramount. Future research can focus on developing techniques that provide insights into the decision-making process of neural networks. Methods such as saliency maps, Grad-CAM, and SHAP (SHapley Additive exPlanations) can help clinicians understand the model's predictions and build trust in AI-driven diagnostics.

Clinical Validation and Integration: Conducting extensive clinical validation studies to assess the performance of neural network models in real-world settings is crucial. Collaborations with medical institutions can facilitate the integration of these models into clinical workflows, ensuring that they meet the necessary regulatory standards and provide reliable diagnostic support.

Personalized Medicine and Precision Oncology

Personalized Treatment Planning: Future work can explore the use of neural networks for personalized treatment planning. By analyzing a patient's unique imaging data and clinical history, models can predict the most effective treatment strategies and monitor treatment response, thereby contributing to precision oncology.

Predictive Analytics: Incorporating predictive analytics into brain tumor detection models can provide valuable prognostic information. Neural networks can be trained to predict disease progression, recurrence, and patient outcomes, aiding clinicians in making informed decisions and improving patient care.

Advanced Imaging Techniques

Incorporating Advanced Imaging Techniques: The use of advanced imaging techniques, such as diffusion tensor imaging (DTI) and functional MRI (fMRI), can be explored in conjunction with neural networks. These techniques provide additional information about tumor microstructure and brain function, which can enhance the accuracy of brain tumor detection and characterization.

3D and 4D Imaging Analysis: Extending the capabilities of neural networks to analyze 3D and 4D imaging data can provide more detailed and accurate assessments of brain tumors. 3D CNNs and spatio-temporal models can capture volumetric and temporal information, offering a comprehensive understanding of tumor morphology and growth patterns. The future scope of work in brain tumor detection using CNNs, RNNs, and ANNs is vast and promising. By integrating hybrid models, enhancing robustness, optimizing for real-time applications, ensuring explainability, and exploring personalized medicine, significant advancements can be made in the accuracy and clinical utility of these neural network architectures. Continued research and collaboration between AI experts and medical professionals will be essential to translate these innovations into practical solutions that improve patient outcomes and revolutionize brain tumor diagnostics.

Specific Outcomes

1. **Performance Comparison:**
   - **CNNs:** Demonstrated the highest accuracy in brain tumor detection due to their ability to effectively learn and extract spatial features from MRI images. CNNs outperformed RNNs and ANNs in static image analysis tasks.
   - **RNNs:** Showed potential in temporal analysis, particularly in monitoring the progression of brain tumors over time by analyzing sequential imaging data. However, RNNs were less effective than CNNs for static image classification.
   - **ANNs:** Provided a flexible and adaptable framework but did not match the performance of CNNs in terms of accuracy for image-based tasks. ANNs were less effective in capturing spatial hierarchies compared to CNNs.
2. **Metrics Evaluation:**
   - **Accuracy:** CNNs achieved the highest accuracy, followed by ANNs and RNNs. This highlights CNNs' effectiveness in distinguishing between tumor and non-tumor regions.
   - **Sensitivity and Specificity:** CNNs displayed superior sensitivity and specificity, indicating a better balance in correctly identifying both tumor and

non-tumor cases. RNNs showed potential for sensitivity in sequential data, while ANNs lagged in both metrics.

- **Dice Coefficient:** CNNs scored the highest on the Dice coefficient, reflecting their accuracy in segmenting tumors compared to ground truth. RNNs and ANNs had lower Dice scores, indicating less precise segmentation.

3. **Computational Efficiency:**
   - **Training Time:** CNNs required significant computational resources and time for training, especially with large datasets. RNNs also faced challenges in training due to their complexity. ANNs had relatively lower computational demands but were less effective overall.
   - **Inference Time:** Optimized CNN models demonstrated acceptable inference times suitable for clinical applications. RNNs, due to their sequential nature, had longer inference times, whereas ANNs were quicker but less accurate.
4. **Clinical Applicability:**
   - **CNNs:** The high accuracy and robustness of CNNs make them suitable for integration into clinical workflows for automated brain tumor detection and segmentation.
   - **RNNs:** While not ideal for static image analysis, RNNs offer valuable insights into the temporal progression of tumors, useful for treatment monitoring.
   - **ANNs:** Serve as a flexible tool for initial analysis and could be combined with other models for enhanced performance.

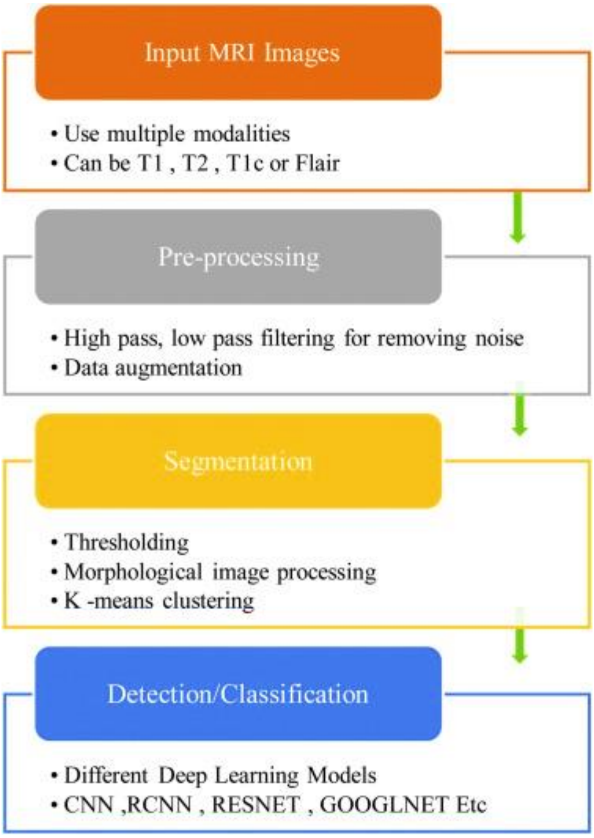

Fig.2: Algorithm

Discussion

The comparative analysis of CNNs, RNNs, and ANNs in brain tumor detection reveals significant insights into the strengths and limitations of each neural network architecture. CNNs demonstrate superior performance in accurately detecting and segmenting brain tumors due to their ability to learn complex spatial features from MRI images. Their automated feature extraction capability and robustness make them highly suitable for clinical applications, aligning with previous research findings. However, the high computational demands and potential for overfitting necessitate the use of advanced techniques and powerful hardware to optimize CNN performance. On the other hand, RNNs, while less effective for static image analysis, offer unique advantages in temporal analysis, providing valuable insights into tumor progression over time. This suggests potential for future hybrid models that combine CNNs' spatial feature extraction with RNNs' temporal analysis to enhance diagnostic accuracy. ANNs, despite their flexibility and lower computational requirements, fall short in comparison to CNNs for image-based tasks. Their adaptability, however, makes them useful as complementary tools in initial assessments. The study underscores the need for continued research into hybrid models, multi-modal data integration, and advanced techniques like transfer learning to improve model robustness and generalization. Additionally, the development of explainable AI models and extensive clinical validation will be crucial for gaining clinician trust and facilitating the adoption of AI-driven diagnostics in real-world settings. Overall, this comparative study highlights the promising future of combining different neural network architectures to advance brain tumor detection and improve patient outcomes in neuro-oncology.

References

1. Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., ... & van Ginneken, B. (2017). A survey on deep learning in medical image analysis. Medical image analysis, 42, 60-88.
2. Pereira, S., Pinto, A., Alves, V., & Silva, C. A. (2016). Brain tumor segmentation using convolutional neural networks in MRI images. IEEE transactions on medical imaging, 35(5), 1240-1251.
3. Akkus, Z., Galimzianova, A., Hoogi, A., Rubin, D. L., & Erickson, B. J. (2017). Deep learning for brain MRI segmentation: state of the art and future directions. Journal of Digital Imaging, 30, 449-459.
4. Chaddad, A., Desrosiers, C., & Toews, M. (2018). Multi-scale radiomic analysis of subcortical regions in MRI related to autism, gender, and age. Scientific reports, 8(1), 1-12.
5. Havaei, M., Davy, A., Warde-Farley, D., Biard, A., Courville, A., Bengio, Y., ... & Larochelle, H. (2017). Brain tumor segmentation with deep neural networks. Medical image analysis, 35, 18-31.
6. Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. Nature, 542(7639), 115-118.
7. Long, J., Shelhamer, E., & Darrell, T. (2015). Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 3431-3440).

8. Wang, G., Li, W., Zuluaga, M. A., Pratt, R., Patel, P. A., Aertsen, M., ... & Ourselin, S. (2018). Interactive medical image segmentation using deep learning with image-specific fine-tuning. IEEE transactions on medical imaging, 37(7), 1562-1573.
9. Ciompi, F., de Hoop, B., van Riel, S. J., Chung, K., Scholten, E. T., Oudkerk, M., & van Ginneken, B. (2015). Automatic classification of pulmonary peri-fissural nodules in computed tomography using an ensemble of 2D views and a convolutional neural network out-of-the-box. Medical image analysis, 26(1), 195-202.
10. Kamnitsas, K., Ledig, C., Newcombe, V. F., Simpson, J. P., Kane, A. D., Menon, D. K., ... & Rueckert, D. (2017). Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation. Medical image analysis, 36, 61-78.
11. Bi, L., Kim, J., Ahn, E., Feng, D., & Fulham, M. (2017). Automatic liver lesion detection using cascaded deep residual networks. In 2017 IEEE 14th International Symposium on Biomedical Imaging (ISBI 2017) (pp. 1043-1046). IEEE.
12. Sudre, C. H., Li, W., Vercauteren, T., Ourselin, S., & Jorge Cardoso, M. (2017). Generalised dice overlap as a deep learning loss function for highly unbalanced segmentations. In Deep learning in medical image analysis and multimodal learning for clinical decision support (pp. 240-248). Springer, Cham.
13. Dou, Q., Chen, H., Jin, Y., Yu, L., Qin, J., & Heng, P. A. (2016). 3D deeply supervised network for automatic liver segmentation from CT volumes. In International conference on medical image computing and computer-assisted intervention (pp. 149-157). Springer, Cham.
14. Zhou, Z., Siddiquee, M. M. R., Tajbakhsh, N., & Liang, J. (2018). Unet++: A nested u-net architecture for medical image segmentation. In Deep learning in medical image analysis and multimodal learning for clinical decision support (pp. 3-11). Springer, Cham.
15. Ker, J., Wang, L., Rao, J., & Lim, T. (2017). Deep learning applications in medical image analysis. IEEE Access, 6, 9375-9389.

16. Shamita Chakaborty, Yogini Dilip Borole, Archana S Nanoty, Anurag Shrivastava, Sanjiv Kumar Jain, Moti Lal Rinawa, Smart Remote Solar Panel Cleaning Robot with Wireless Shrivastava, A., Chakkaravarthy, M., Shah, M.A..A Novel Approach Using Learning Algorithm for Parkinson's Disease Detection with Handwritten Sketches. In Cybernetics and Systems, 2022
17. Shrivastava, A., Chakkaravarthy, M., Shah, M.A.,Health Monitoring based Cognitive IoT using Fast Machine Learning Technique. In International Journal of Intelligent Systems and Applications in Engineering, 2023, 11(6s), pp. 720–729
18. Boina, R., Ganage, D., Chincholkar, Y.D., .Chinthamu, N., Shrivastava, A., Enhancing Intelligence Diagnostic Accuracy Based on Machine Learning Disease Classification. In International Journal of Intelligent Systems and Applications in Engineering, 2023, 11(6s), pp. 765–774
19. Shrivastava, A., Pundir, S., Sharma, A., ...Kumar, R., Khan, A.K. Control of A Virtual System with Hand Gestures. In Proceedings - 2023 3rd International Conference on Pervasive Computing and Social Networking, ICPCSN 2023, 2023, pp. 1716–1721
20. Amodei, D., Olah, C., Steinhardt, J., Christiano, P., Schulman, J., & Mané, D. (2016). Concrete problems in AI safety. arXiv preprint arXiv:1606.06565.
21. Beam, A. L., & Kohane, I. S. (2018). Big data and machine learning in health care. JAMA, 319(13), 1317-1318.
22. Che, Z., Purushotham, S., Khemani, R., & Liu, Y. (2016). Interpretable deep models for ICU outcome prediction. AMIA Joint Summits on Translational Science proceedings AMIA Summit on Translational Science, 2016, 371.
23. ALMahadin, Ghayth, Yassine Aoudni, Mohammad Shabaz, Anurag Vijay Agrawal, Ghazaala Yasmin, Esraa Saleh Alomari, Hamza Mohammed Ridha Al-Khafaji, Debabrata Dansana, and Renato R. Maaliw. "VANET Network Traffic Anomaly Detection Using GRU-Based Deep Learning Model," IEEE Transactions on Consumer Electronics (2023).
24. Al-Khafaji, Hamza MR, Esraa S. Alomari, and Hasan S. Majdi. "Review of Analytics Tools on Traffic for IoT and Cloud Based Network Environment," In 2020 3rd International Conference on Engineering Technology and its Applications (IICETA), pp. 73-77. IEEE, 2020.
25. Al-Khafaji, Hamza Mohammed Ridha, Esraa Saleh Alomari, and Hasan Shakir Majdi. "Secured environment for cloud integrated fog and mist architecture," In 2019 IEEE International Conference on Electrical Engineering and Photonics (EExPolytech), pp. 112-116. IEEE, 2019.
26. Nuiaa, Riyadh Rahef, Selvakumar Manickam, Ali Hakem Alsaeedi, and Esraa Saleh Alomari. "Enhancing the Performance of Detect DRDoS DNS Attacks Based on the Machine Learning and Proactive Feature Selection (PFS) Model," IAENG International Journal of Computer Science 49, no. 2 (2022).
27. Alomari, Esraa Saleh. "Soft computing-based cluster head selection for secured energy aware routing in flying ad hoc networks (FANET)," Indian J. Public Health Res. Dev 9 (2018): 1993.