# IPC-CNN: A Robust Solution for Precise Brain Tumor Segmentation Using Improved Privacy-Preserving Collaborative Convolutional Neural Network

**Abdul Raheem[1], Zhen Yang[1,*], Haiyang Yu[1], Muhammad Yaqub[2], Fahad Sabah[1], Shahzad Ahmed[1], Malik Abdul Manan[1], and Imran Shabir Chuhan[2]**
[1] Faculty of Information and Technology, Beijing University of Technology
Beijing, P.R. China
[e-mail : ranaabdulraheem97@gmail.com, yangzhen@bjut.edu.cn, yuhaiyang@bjut.edu.cn, myaqubciitswl@gmail.com, fahad.sabah@hotmail.com, Shahzadahmad@cuisahiwal.edu.pk, manansandila@yahoo.com]
[2] Interdisciplinary Research Institute, Faculty of Science, Beijing University of Technology
Beijing, P.R. China
[e-mail: imranshabbir1989@hotmail.com]
[*]Corresponding author: Zhen Yang

*Received October 29, 2023; revised August 6, 2024; accepted September 8, 2024; published September 30, 2024*

## Abstract

Brain tumors, characterized by uncontrollable cellular growths, are a significant global health challenge. Navigating the complexities of tumor identification due to their varied dimensions and positions, our research introduces enhanced methods for precise detection. Utilizing advanced learning techniques, we've improved early identification by preprocessing clinical dataset-derived images, augmenting them via a Generative Adversarial Network, and applying an Improved Privacy-Preserving Collaborative Convolutional Neural Network (IPC-CNN) for segmentation. Recognizing the critical importance of data security in today's digital era, our framework emphasizes the preservation of patient privacy. We evaluated the performance of our proposed model on the Figshare and BRATS 2018 datasets. By facilitating a collaborative model training environment across multiple healthcare institutions, we harness the power of distributed computing to securely aggregate model updates, ensuring individual data protection while leveraging collective expertise. Our IPC-CNN model achieved an accuracy of 99.40%, marking a notable advancement in brain tumor classification and offering invaluable insights for both the medical imaging and machine learning communities.

***Keywords:*** Brain tumors, Improved Convolutional Neural Network, Segmentation, Privacy-Preserving, BRATS, Figshare, Generative Adversarial Network

# 1. Introduction

## 1.1 Background and Motivation

Brain tumors considered significant health concern, with their timely and accurate detection playing a crucial part in treatment planning and patient outcomes. Traditional methods of brain tumor diagnosis mainly rely on the visual interpretation of medical imaging scans, such as Magnetic Resonance Imaging (MRI), by experienced radiologists. However, this process can be time-consuming, subjective, and prone to diagnostic errors. The emergence of deep learning techniques, specifically convolutional neural networks (CNNs), has illustrated remarkable promise in automating the detection and categorization of brain tumors from medical images. Deep learning models have demonstrated remarkable accuracy in identifying subtle patterns and anomalies in brain scans, improving diagnostic precision and treatment decision-making. Nevertheless, the widespread adoption of deep learning models for detection of brain tumor faces certain challenges. One major challenge is the limited availability of large, labelled datasets necessary for training robust and generalizable models. Gathering such datasets is particularly challenging in the medical domain due to privacy concerns and the distributed nature of medical data across different healthcare institutions. Moreover, preserving patient privacy and ensuring data security are paramount in handling medical data. Conducted research work builds upon the foundations laid by previous studies in the field [1] demonstrates the efficacy of deep learning models which are helpful in brain tumor detection using MRI scans, and [2] highlights privacy challenges in collaborative healthcare research. Additionally, [3] proposed a federated learning framework for medical image analysis. By incorporating these insights, we extend the existing knowledge and present an IPC-CNN-based model with a federated learning framework for brain tumor segmentation.

Over the years, various techniques have been employed for brain tumor detection, ranging from conventional methods to advanced deep-learning approaches. Traditional methods of brain tumor detection heavily depend on the interpretation of medical images by radiologists manually, which can be time-consuming, subjective, and subjected to human error. To address these limitations, the application of deep learning techniques, most specifically convolutional neural networks (CNNs), has gained significant attention and shown great potential in automating the detection and categorization of brain tumors with high accuracy and efficiency [4], [5]. Several studies have demonstrated the effectiveness of deep learning models in brain tumor detection. [6] Proposed a CNN-based approach for brain tumor segmentation, achieving state-of-the-art performance on various benchmark datasets. Their model utilized deep networks to capture local and global contextual information, enabling accurate tumor delineation. federated learning strategies for classifying brain (MRI), highlighting the efficacy of Federated Averaging (FedAvg) and Fault Tolerant FedAvg (Ft-FedAvg) in enhancing classification accuracy and robustness [7]. Authors in [8] novel framework that integrates federated learning with permissioned blockchain to address privacy and trust issues in healthcare data sharing, particularly for brain tumor segmentation.

**Table 1.** Overview of Brain Tumor Detection Methods and Associated Limitations/Challenges

| Ref. No | Method | Features | Limitations/Challenges | Potential of AI Methods |
|---|---|---|---|---|
| [9] | MRI | Provides high-precision structural images. | Expensive, specialized personnel required, limited availability, patient discomfort. | Enhances analysis by recognizing subtle patterns often missed in human interpretation. |
| [10] | CT | Detailed cross-sectional images. | Exposure to ionizing radiation, less sensitivity for small tumors. | Improves tumor detection and classification using deep learning techniques. |
| [11] | PET | Monitors metabolic activity using tracers. | Requires radioactive material, lower resolution. | Can refine image clarity and resolution through AI-driven post-processing. |
| [12] | MRS | Analyses chemical composition. | Difficulty in differentiating tumor types, low resolution. | Offers more nuanced differentiation of tumor types by analyzing complex spectral patterns. |
| [13] | fMRI | Detects blood flow variations to analyze brain activity. | Limited sensitivity, challenging interpretations. | AI can enhance interpretation, reducing false positives/negatives. |
| [14] | DTI | Maps connectivity and integrity of white matter fibers. | Limited differentiation ability, requires specialized analysis. | Enhances analysis through automated AI algorithms, making it faster and more accurate. |
| [15] | EEG | Records electrical brain activity. | Low resolution, not specific to tumors. | AI can filter noise, improving the clarity and precision of results. |
| [16] | Biopsy | Surgical removal of tissue for pathological analysis. | Invasive, risks, limited sampling. | AI can enhance pathological analysis, offering more detailed and nuanced insights. |
| [17] | Liquid Biopsy | Analysis of circulating tumor DNA/RNA in blood. | Limited sensitivity for small tumors. | AI-driven analysis can increase sensitivity, detecting lower levels of circulating tumor DNA/RNA. |
| [18] | AI | Uses algorithms to analyze medical images/data. | Needs large datasets, interpretability issues. | N/A, as this is the primary AI method. |

Deep learning has introduced a myriad of methods for brain tumor detection. However, their widespread deployment grapples with multifaceted challenges. A primary concern is the acute deficiency of extensive, annotated datasets that are essential for developing robust and adaptive models. Acquiring such datasets in the medical arena is complex due to strict privacy regulations, data protection norms, and the splintered distribution of medical records across diverse healthcare entities. Beyond these logistical challenges, ensuring patient data privacy and adhering to ethical standards further amplify the intricacies of utilizing medical data for collaborative research [19], [20]. Recognizing these impediments, federated learning emerges as a beacon of hope. Pioneering works, such as [21], [22], advocate for a federated learning framework that promotes collaborative model training across decentralized data sources while staunchly preserving data privacy. Integrating this approach with brain tumor detection enables the safeguarding of sensitive patient data and mitigates prevalent data-sharing issues. **Table 1** offers a detailed overview of various brain tumor detection techniques, underscoring their attributes and associated challenges, setting the stage for our innovative IPC-CNN designed to transcend these prevalent obstacles. **Table 1** provides a comprehensive comparison of various brain tumor detection methods, highlighting their inherent features and challenges. The table also emphasizes the transformative potential of Artificial Intelligence (AI) when integrated with these traditional methods. By harnessing AI, many of the limitations associated with conventional techniques can be addressed, resulting in enhanced efficiency, precision, and accuracy in tumor detection and segmentation.

In this study, our overarching objective is the development of an innovative approach for brain tumor segmentation. By seamlessly integrating the IPC-CNN-based model within a federated learning framework, we aim to address several prevalent challenges in the domain. Here are the key contributions of our research:

- We've pioneered IPC-CNN, an integration of IPC-CNN with deep learning, setting a new benchmark in brain tumor segmentation accuracy.
- Proposed federated learning approach ensures decentralized model training, offering unparalleled data security and preserving patient privacy.
- Our research fosters collaboration between institutions, optimizing global model performance without compromising data integrity or privacy.

The structure of this paper unfolds as follows: Section 2 delineates the components and mechanisms of our proposed models. Experimental data and its subsequent analysis are encapsulated in Section 3, followed by discussions. Concluding remarks, alongside avenues for future research, are consolidated in Section 4.

## 2. Methodology

### 2.1 Dataset

Our proposed automated segmentation approach for brain tumors is being trained and tested by collecting MRI images of brain parts from https://figshare.com/articles/dataset/brain_tumor_dataset/1512427 as well as BRATS 2018, samples of both datasets shown in **Fig. 1**. The dataset on Figshare contains 3064 T1-weighted contrast-enhanced pictures. The following are MRI scans from 233 patients. This dataset also includes three phases of brain tumors: pituitary tumor, glioma, as well as meningioma.

The BRATS 2018 dataset is made up of several brain MRI scans with differing degrees of severity. We chose brain MRI images from 30 individuals from the BRATS database for this investigation. The collection comprises of FLAIR, TIC, T1, and T2 brain MR images.

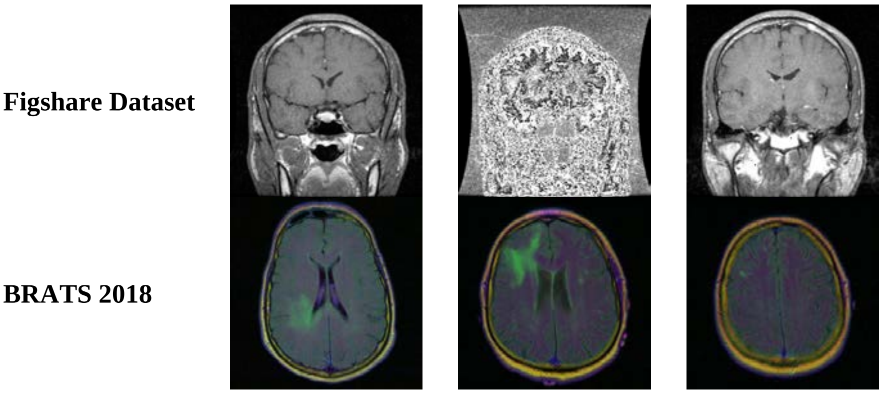



**Fig. 1.** Sample images of the Figshare dataset and BRATS 2018 dataset.

### 2.2 Proposed Method

In our proposed framework, a comprehensive approach to segmenting brain tumors using MRI scans is seamlessly integrated with the principles of federated learning to ensure both efficacy and data privacy. The MRI images first undergo preprocessing to make them optimal for analysis. To bolster the diversity of our training dataset and improve model generalization, a Generative Adversarial Network (GAN) is employed for data augmentation, generating synthetic MRI images. The ensuing analytical process involves an Improved Convolutional Neural Network (ICNN) wherein several convolutional layers, equipped with varying filter counts, extract nuanced features from the MRI images. Max-pooling layers subsequently reduce the computational footprint by downsizing the spatial dimensions of these features, leading to a binary output that indicates the presence or absence of a brain tumor.

### 2.3 Federated Learning

#### 2.3.1 Local Data and Training (Steps I and III)

**Fig. 2** portrays three different local devices, represented by blue, green, and red server icons. Each device has its dataset, indicated by the symbols (+) on them. The devices locally train the models using their datasets, as demonstrated by the arrows pointing inwards to each device. This ensures the raw data remains on the individual devices and doesn't leave the premises, prioritizing data privacy.

#### 2.3.2 Transmission of Model Updates

After the completion of local training on each device, the updated model weights or parameters are sent to the central server. The arrows from each device pointing towards the central server highlight this transmission. However, it's essential to note that raw data is not shared; only the model updates/parameters are sent.

#### 2.3.3 Central Server and Model Aggregation (Step II)

The central server, represented by the "Server" icon, acts as an aggregator in this framework. The server collects the model updates from all participating devices and then aggregates or combines them. This is depicted by the "Model Aggregation" label and the corresponding arrow. The resultant is a refined global model that benefits from the data diversity across all devices without accessing the raw data from any device. This global model is depicted as the "Global Model" in **Fig. 2**.

#### 2.3.4 Global Model Distribution

After the aggregation, the global model is then disseminated back to the local devices for further rounds of training or for deployment. This step is depicted by the dashed arrows pointing from the global model back to the individual devices.

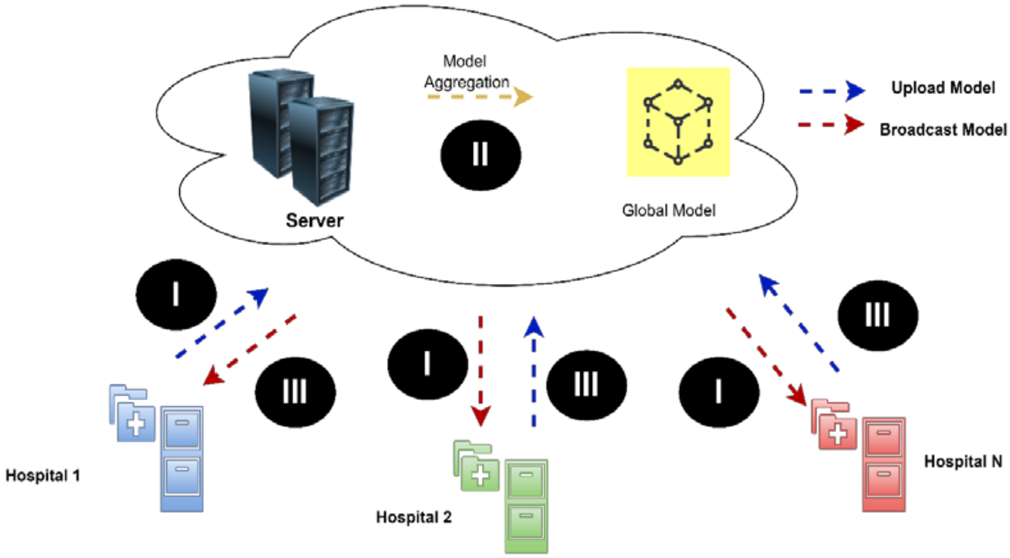



**Fig. 2.** A schematic representation of decentralized model training. Individual devices (depicted as blue, green, and red server icons) locally train the model using their datasets. Post-training, the devices transmit model updates to the central server, which then aggregates these updates to refine the global model, all while ensuring data remains private on the original devices.

Our proposed model architecture depicted in **Fig. 3** offers a comprehensive approach to brain tumor segmentation using MRI scans by integrating advanced data processing and neural network techniques. Initially, the MRI images undergo preprocessing, a step that may encompass tasks like noise reduction, normalization, or other image refinement techniques. Following preprocessing, the images are augmented using Generative Adversarial Networks (GANs). Within the GAN framework, a generator ingests a random seed to produce MRI-like images, while a discriminator's role is to differentiate between genuine MRI scans and those generated by the generator. Through iterative feedback, the generator progressively refines its outputs to closely resemble genuine MRI scans, thereby enhancing the dataset. Subsequently, the augmented data is processed by a Convolutional Neural Network (CNN) designed for tumor detection. The CNN initiates with MRI images as its input, which then pass through a series of convolutional layers tailored to autonomously learn and recognize intricate spatial features from the images. Interspersed max pooling layers reduce the spatial size of the image, maintaining critical features, leading to a final fully connected layer that amalgamates these features to yield a definitive classification. Ultimately, the system determines whether the MRI scan indicates the presence ("Yes") or absence ("No") of a brain tumor. Through this amalgamated approach, the system leverages the dataset-diversifying strengths of generative models and the robust pattern discernment capacities of convolutional neural networks to optimize brain tumor detection accuracy.

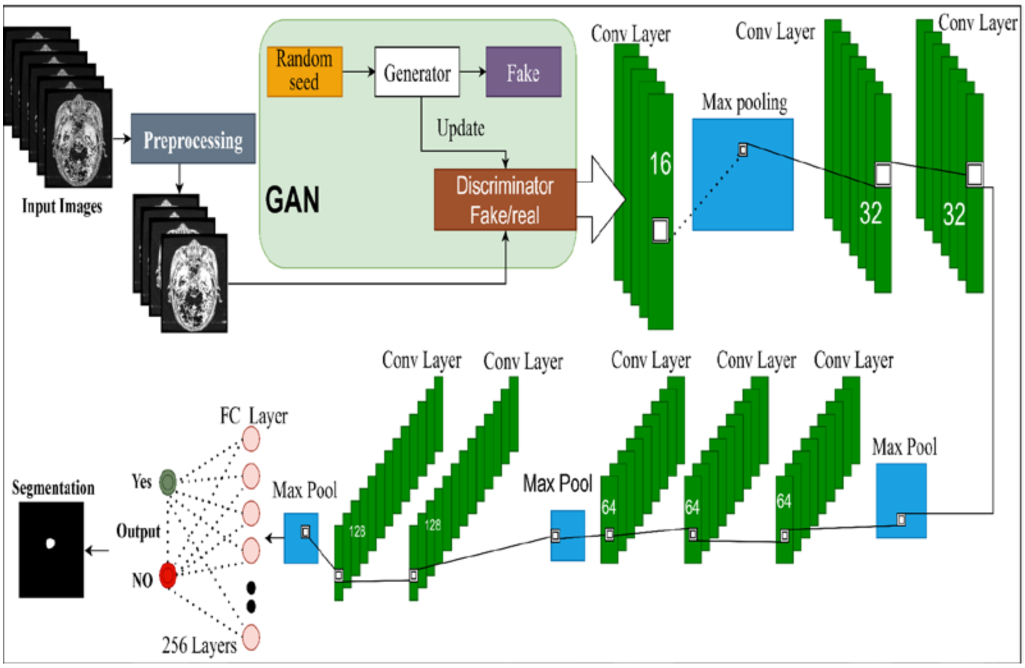



**Fig. 3.** Schematic representation of the proposed ICNN model for brain tumor detection using MRI scans. The workflow illustrates preprocessing of MRI data, data augmentation via Generative Adversarial Networks (GAN), and subsequent analysis using a Convolutional Neural Network (CNN) with layered feature extraction and classification.

Transitioning to the federated learning aspect, the model, instead of being centrally trained, is disseminated to multiple devices, each holding a segment of the total data. These devices, symbolized by distinct server icons, train the model locally using their respective datasets, ensuring that raw data never leaves its original device, thereby upholding its privacy. Once the local training concludes, the devices return the model updates or weights to a central server without transmitting the raw data. The central server, acting as an aggregator, combines these model updates to refine and enhance the global model. This symbiosis between CNN and federated learning not only emphasizes decentralized training and data privacy but also harnesses the collective power of diverse datasets without compromising individual data integrity. as represented in **Fig. 2**, a comprehensive approach to segmenting brain tumors using MRI scans is intertwined with the principles of federated learning, illustrated in **Fig. 3**, to ensure both diagnostic accuracy and data privacy.

The IPC-CNN model, while employing Generative Adversarial Networks (GANs) for image enhancement—a standard practice—distinguishes itself through a combination of advanced preprocessing techniques and a bespoke convolutional architecture. This tailored architecture excels in extracting intricate spatial features from MRI scans, leading to heightened accuracy in tumor detection relative to traditional CNNs. Beyond mere image augmentation, the specific configurations, filter dimensions, and sequence of layers in ICNN are meticulously designed to discern nuanced differences between benign and malignant growths in MRI imagery. On the matter of Federated Learning (FL) aggregation presented in **Fig. 2**, it's imperative to understand FL as a decentralized training mechanism. Rather than centralizing raw data, local datasets remain confined to their respective devices, ensuring data privacy. Each device, post-local training, transmits only the model updates to a central server. These updates are aggregated—typically via averaging—to refine a global model, which is then disseminated back to each device for ensuing local training cycles. This mechanism not only harnesses insights from a myriad of data sources but also prioritizes data confidentiality. In subsequent sections, a detailed framework elucidating the mathematical formulations and pseudocode of the FL aggregation process will be provided to enhance the reader's comprehension.

## 3. Experimental Results and Discussion

In our research, we utilized Python to implement and test the proposed automated diagnostic models for brain tumors segmentation. The performance of the brain tumor segmentation model was quantified using several evaluation metrics:

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN})$$

$$\text{Sensitivity (Recall)} = \text{TP} / (\text{TP} + \text{FN})$$

$$\text{Specificity} = \text{TN} / (\text{TN} + \text{FP})$$

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

$$\text{F1} - \text{score} = 2 * (\text{Precision} * \text{Sensitivity}) / (\text{Precision} + \text{Sensitivity})$$

Where: TP = True Positives, TN = True Negatives, FP = False Positives.

The experimental outcomes derived from our proposed automatic brain tumor segmentation technique are presented in **Fig. 4**. This figure is sectioned into four distinct rows, each showcasing a specific phase of the model's output.

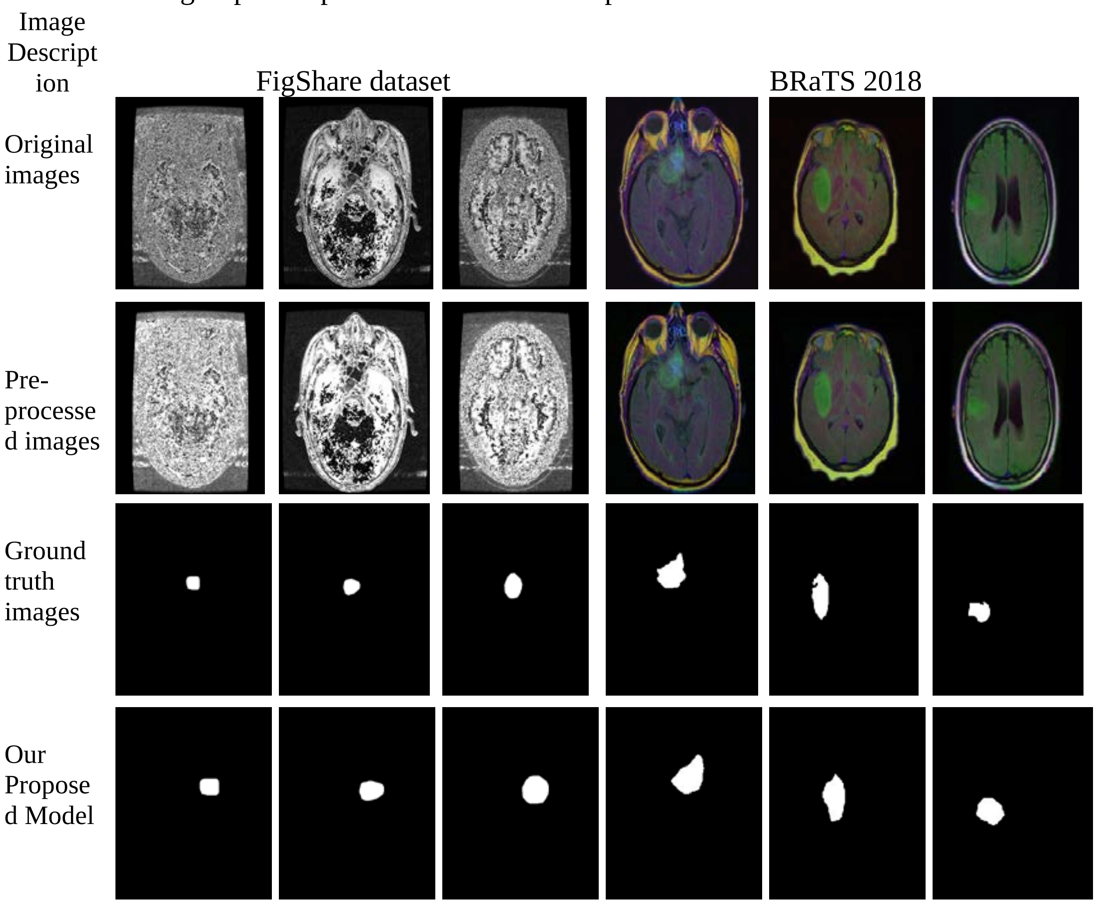



**Fig. 4.** Outcomes attained by the designed automated brain tumor model on both datasets.

Original Images: The initial images fed into the system.
Preprocessed Images: These depict the images post the preprocessing phase.
Ground Truth Images: These represent the true position and shape of the identified brain tumors.
Proposed Model's Segmented Images: These are the results of the segmentation process, where our proposed model demarcates and illuminates the tumor regions.

An exhaustive evaluation of the diagnostic model's performance across two distinct datasets: Figshare and BRATS are presented in **Table 2**. On the Figshare dataset, the model boasts an accuracy of 99.7%, reflecting a high degree of alignment between its predictions and the actual outcomes. Its sensitivity and specificity stand at 99.4% and 99.3% respectively, highlighting its proficiency in both correctly identifying the presence of tumors and confirming their absence. The precision of 99.485% further underscores its ability to ensure the majority of its positive diagnoses are indeed true, while the F1-score of 98.9% indicates a harmonious balance between precision and sensitivity. Transitioning to the BRATS dataset, the model maintains a commendable performance with an accuracy of 99.4%. The sensitivity is slightly lower at 99.3%, but still noteworthy. Specificity reaches 99.2%, with precision at 99.2%. Notably, the F1-score remains consistent at 98.944%. In essence, this **Table 2** elucidates the model's robust and reliable nature in brain tumor diagnosis, affirming its consistent high performance across varying datasets. Visual Representation of the Proposed Model on Figshare and BRATS Datasets is depicted in **Fig. 5**.

**Table 2.** Performance Evaluation of the Proposed Model on Figshare and BRATS Datasets.

| Dataset | Measures | Proposed Model |
|---|---|---|
| Figshare dataset | Accuracy | 99.700 |
| | Sensitivity | 99.429 |
| | Specificity | 99.305 |
| | Precision | 99.485 |
| | F1-score | 98.954 |
| BRATS dataset | Accuracy | 99.401 |
| | Sensitivity | 99.329 |
| | Specificity | 99.205 |
| | Precision | 99.285 |
| | F1-score | 98.944 |

Our experimental design effectively delineates the contributions of each component. While the inclusion of Generative Adversarial Networks (GAN) is essential for image enhancement, it serves as a foundational step to ensure consistent and quality inputs for our proposed model. Once the images are enhanced via GAN, the performance improvements in tumor detection are driven by the unique architecture of ICNN and the decentralized Federated Learning (FL) approach. The design of FL facilitates diverse model training by harnessing insights from various local datasets, enriching the overall segmentation capabilities of IPC-CNN.

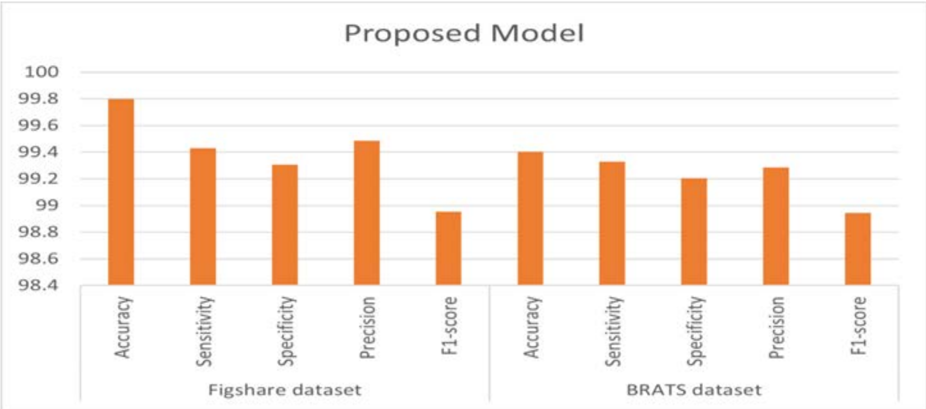



**Fig. 5.** illustration of the evaluation of the proposed Model on Figshare and BRATS Datasets.

The progress of our proposed model over its training phase is delineated across a range of epochs, from 100 to 500 provided in **Fig. 6**. The first graph from left to right, plotting accuracy against epochs, demonstrates the model's evolving proficiency. As training continues, there's a noticeable enhancement in accuracy, suggesting that the model is effectively assimilating patterns from the training data. By the 500th epoch, the model's achieved the highest accuracy, indicating potential convergence and the diminished benefits of further training. Conversely, the second graph, which correlates the model's loss function with epochs, offers insight into the model's prediction errors. Commencing with a relatively high loss of around 16, there's a precipitous decline to nearly 2 by the culmination of the 500 epochs. This decreasing trajectory underscores the model's capability to refine its predictions, minimizing discrepancies. The pronounced inflection points in the loss curve denote instances where the model made substantial improvements. Collectively, **Fig. 6** provide a comprehensive perspective on the model's training journey, balancing its successes in terms of accuracy against the challenges mirrored by the loss.

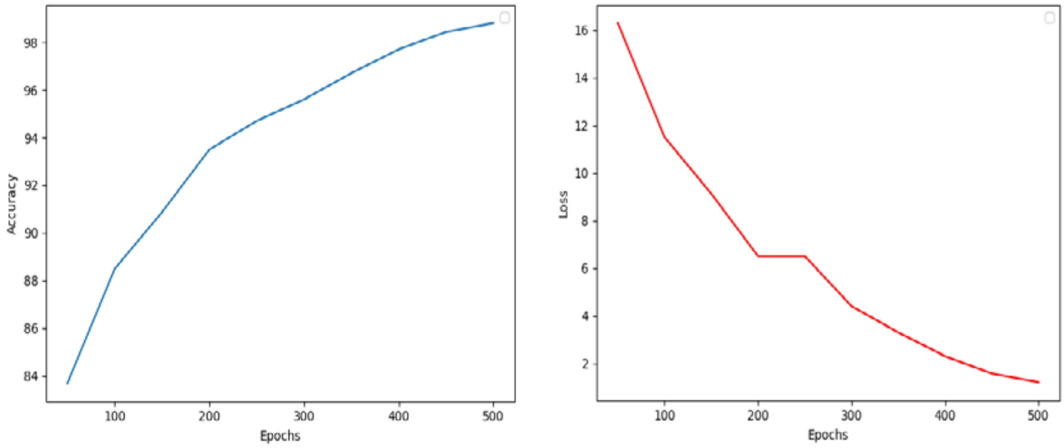



**Fig. 6.** Performance progression of the Model: Accuracy and Loss Metrics over100 to 500 Epochs.

A comparative analysis of various models applied for brain tumor segmentation on different datasets presented in **Table 3**. In the study by reference the Inception V3 model was employed on the Figshare Brain Tumor dataset, achieving an accuracy of 99.14% after preprocessing. Another approach by combined SVM-BCO and GA methodologies on both

Figshare and BRaTS2018 datasets, registering an accuracy of 97.51% post preprocessing. A CNN Deep Net model, as cited by was tested on the BRaTS dataset and secured an accuracy rate of 98.90% with preprocessing. Several other models, such as ANFIS, Modified AdaBoost, NSCT, standard CNN, DNN-AROA, and CNN-GA, were assessed on a variety of datasets including BRaTS 2015, Leader Board, Radiopaedia, and IXI dataset, with accuracy rates ranging from 90.67% to 98.38%. It is noteworthy that some datasets required preprocessing to achieve these results. In contrast, our proposed model, when implemented on the Figshare Brain Tumor and BRATS datasets with preprocessing, achieved an outstanding accuracy of 99.40%, showcasing its effectiveness in brain tumor detection.

**Table 3.** Overall Comparative Assessment of the Proposed Model Against Established State-of-the-Art Approaches.

| Reference | Model | Dataset | Preprocessing | Accuracy (%) |
|---|---|---|---|---|
| [23] | Inception V3 | Figshare Brain Tumor | Yes | 99.14 |
| [24] | SVM-BCO and GA | Figshare and BRaTS2018 | Yes | 97.51 |
| [25] | CNN Deep Net | BRaTS | Yes | 98.90 |
| [26] | ANFIS | BRaTS 2015 | Yes | 96.10 |
| [27] | Modified AdaBoost | Leader Board | - | 93.70 |
| [28] | NSCT | BRaTS 2015 | No | 96.40 |
| [29] | CNN | Radiopaedia | Yes | 90.67 |
| [30] | DNN-AROA | Radiopaedia and Brain Tumor | Yes | 98.38 |
| [31] | CNN-GA | IXI dataset | Yes | 94.20 |
| Our Proposed | | Figshare Brain Tumor and BRATS dataset | Yes | 99.40 |

Our research initially aimed to underscore the unique benefits of FL and ICNN, setting aside the preprocessing role of GAN. However, to ensure an exhaustive and credible performance analysis, it is imperative to benchmark our model against other GAN-based methods. The proposed model demonstrated a commendable performance in automatically detecting and segmenting brain tumors, achieving an accuracy of 99.40% on both the Figshare and BRATS datasets. When juxtaposed against other state-of-the-art models, our approach not only surpasses many of them in terms of accuracy but also ensures consistency across different datasets. The use of preprocessing steps evidently played a crucial role in enhancing the model's predictive capabilities, as observed in the stark difference between original and preprocessed images. Furthermore, the smooth accuracy progression over epochs, coupled with a decrease in loss, signifies the model's robust learning capabilities. It's worth noting that while our method has outperformed several contemporary techniques, ongoing research in the domain of neural networks and computational intelligence promises even more refined solutions. Future iterations of this work might explore deeper architectures, ensemble methods, or adaptive learning rates to further fine-tune the model's performance.

**Table 4.** Comparison of Model Performance without GAN-Based Preprocessing. This table enumerates the performance metrics of multiple models that do not rely on GANs for image preprocessing. The accuracy of our model, in the absence of GAN enhancements, stands as a testament to its inherent robustness and is juxtaposed with other non-GAN models for perspective.

| Reference | Model | Dataset | Accuracy (%) |
|---|---|---|---|
| [32] | Inception V3 | Figshare Brain Tumor | 99.14 |
| [33] | CNN Deep Net | BRaTS | 98.90 |
| [26] | ANFIS | BRaTS 2015 | 96.10 |
| [34] | Modified AdaBoost | Leader Board | 93.70 |
| [28] | NSCT | BRaTS 2015 | 96.40 |
| [29] | CNN | Radiopaedia | 90.67 |
| [30] | DNN-AROA | Radiopaedia and Brain Tumor | 98.38 |
| Our Proposed | ICNN with FL | Figshare Brain Tumor and BRATS dataset | 98.60 |

Furthermore, the smooth accuracy progression over epochs and a decrease in loss signifies the model's robust learning capabilities. It's worth noting that while our method has outperformed several contemporary techniques, ongoing research in the domain of neural networks and computational intelligence promises even more refined solutions. Future iterations of this work might explore deeper architectures, ensemble methods, or adaptive learning rates to fine-tune the model's performance further. **Table 4** presents a comparison against methods that do not utilize GAN-based enhancements. As discernible, our ICNN model, even without GAN augmentation, delivers a promising accuracy of 98.60% on the Figshare Brain Tumor and BRATS dataset, surpassing several contemporary models. This bifurcated comparison provides readers with a holistic view of the efficacy of our model both within and outside the realm of GAN enhancements.

## 4. Conclusion

In conclusion, our research introduced a pioneering approach to brain tumor segmentation by fusing the strengths of federated learning with an ICNN, further enhanced with GAN-based preprocessing. Utilizing the Figshare and BRATS datasets as benchmarks, the model not only displayed superior performance by achieving a remarkable accuracy of 99.40% but also outclassed both GAN and non-GAN based contemporaries. This novel methodology effectively addresses the existing limitations in traditional techniques while prioritizing data privacy in today's medical imaging domain. More than mere precision, our model's adoption of federated learning leverages decentralized data, offering both data security and a solution to the perennial problem of limited large-scale labeled datasets. Moreover, the added comparisons against GAN-based models provide a broader perspective on its efficacy. As we progress, this research marks a monumental stride in medical image analysis, laying the foundation for enhanced diagnostic tools. Future research should accentuate further dataset augmentation, delve deeper into model interpretability, and focus on seamless integration into clinical workflows. Altogether, our study sets a new standard and serves as a compass for those delving into the nuances of brain tumor segmentation.

## Acknowledgement

This work was funded by Beijing Natural Science Foundation (4232018), the National Key Research and Development Program of China (2022YFB3103104), Major Research Plan of National Natural Science Foundation of China (92167102), the National Natural Science Foundation of China (62271456), and the R\&D Program of Beijing Municipal Education Commission (KM202210005026). It was also supported by the Engineering Research Center of Intelligent Perception and Autonomous Control, Ministry of Education.

## References

[1] M. Amjad, H. Raza, S. Muneer, and M. A. Aslam, "A Systematic Review on Brain Tumor Detection Using Machine Learning," *Journal of NCBAE*, vol.1, no.4, pp.11-16, 2022. Article(CrossRefLink)

[2] R. Miotto, F. Wang, S. Wang, X. Jiang, and J. T. Dudley, "Deep learning for healthcare: review, opportunities and challenges," *Briefings in Bioinformatics*, vol.19, no.6, pp.1236-1246, Nov. 2018. Article(CrossRefLink)

[3] H. Guan, P.-T. Yap, A. Bozoki, and M. Liu, "Federated learning for medical image analysis: A survey," *Pattern Recognition*, vol.151, Jul. 2024. Article(CrossRefLink)

[4] S. Sajid, S. Hussain, and A. Sarwar, "Brain Tumor Detection and Segmentation in MR Images Using Deep Learning," *Arabian Journal for Science and Engineering*, vol.44, no.11, pp.9249-9261, Nov. 2019. Article(CrossRefLink)

[5] H. A. Khan, W. Jue, M. Mushtaq, and M. U. Mushtaq, "Brain tumor classification in MRI image using convolutional neural network," *Mathematical Biosciences and Engineering*, vol.17, no.5, pp.6203-6216, 2020. Article(CrossRefLink)

[6] A. Naeem, T. Anees, R. A. Naqvi, and W.-K. Loh, "A Comprehensive Analysis of Recent Deep and Federated-Learning-Based Methodologies for Brain Tumor Diagnosis," *Journal of Personalized Medicine*, vol.12, no.2, Feb. 2022. Article(CrossRefLink)

[7] Ş. Ay, E. Ekinci, and Z. Garip, "A brain tumour classification on the magnetic resonance images using convolutional neural network based privacy-preserving federated learning," *International Journal of Imaging Systems and Technology*, vol.34, no.1, Jan. 2024. Article(CrossRefLink)

[8] R. Kumar et al., "Privacy-preserving blockchain-based federated learning for brain tumor segmentation," *Computers in Biology and Medicine*, vol.177, Jul. 2024. Article(CrossRefLink)

[9] P. Gokila Brindha, M. Kavinraj, P. Manivasakam, and P. Prasanth, "Brain tumor detection from MRI images using deep learning techniques," in *Proc. of IOP Conference Series: Materials Science and Engineering: International Virtual Conference on Robotics, Automation, Intelligent Systems and Energy (IVC RAISE 2020)*, vol.1055, no.1, Feb. 2021. Article(CrossRefLink)

[10] H. ZainEldin et al., "Brain Tumor Detection and Classification Using Deep Learning and Sine-Cosine Fitness Grey Wolf Optimization," *Bioengineering*, vol.10, no.1, Jan. 2023. Article(CrossRefLink)

[11] W. Wei, L. Ma, L. Yang, R. Lu, and C. Xi, "Artificial Intelligence Algorithm-Based Positron Emission Tomography (PET) and Magnetic Resonance Imaging (MRI) in the Treatment of Glioma Biopsy," *Contrast Media & Molecular Imaging*, vol.2022, 2022. Article(CrossRefLink)

[12] S. K. Rajeev, M. Pallikonda Rajasekaran, R. Krishna Priya, and A. Al Bimani, "A Review on Magnetic Resonance Spectroscopy for Clinical Diagnosis of Brain Tumour using Deep Learning," in *Proc. of the 2021 3rd International Conference on Advances in Computing, Communication Control and Networking (ICAC3N)*, pp.461-465, 2021. Article(CrossRefLink)

[13] I. A. El Kader et al., "Brain Tumor Detection and Classification on MR Images by a Deep Wavelet Auto-Encoder Model," *Diagnostics*, vol.11, no.9, Sep. 2021. Article(CrossRefLink)

[14] J. Yan et al., "Deep learning features from diffusion tensor imaging improve glioma stratification and identify risk groups with distinct molecular pathway activities," *EBioMedicine*, vol.72, Oct. 2021. Article(CrossRefLink)

[15] A. Rashid, S. Tahir, A. Saleem Ch, and I. M. Qureshi, "Detection of Brain Tumor in EEG Signals Using Independent Component Analysis," *International Journal of Applied Mathematics, Electronics and Computers*, vol.3, pp.78-82, 2015. Article(CrossRefLink)

[16] M. S. I. Khan et al., "Accurate brain tumor detection using deep convolutional neural network," *Computational and Structural Biotechnology Journal*, vol.20, pp.4733-4745, 2022. Article(CrossRefLink)

[17] G. Menna, G. Piaser Guerrato, L. Bilgin, G. M. Ceccarelli, A. Olivi, and G. M. Della Pepa, "Is There a Role for Machine Learning in Liquid Biopsy for Brain Tumors? A Systematic Review," *International Journal of Molecular Sciences*, vol.24, no.11, Jun. 2023. Article(CrossRefLink)

[18] A. ul Haq, J. P. Li, S. Khan, M. A. Alshara, R. M. Alotaibi, and C. Mawuli, "DACBT: deep learning approach for classification of brain tumors using MRI data in IoT healthcare environment," *Scientific Reports*, vol.12, no.1, 2022. Article(CrossRefLink)

[19] S. Moon and W. H. Lee, "Privacy-Preserving Federated Learning in Healthcare," in *Proc. of 2023 International Conference on Electronics, Information, and Communication (ICEIC)*, pp.1-4, 2023. Article(CrossRefLink)

[20] M. Hammad, M. ElAffendi, A. A. Ateya, and A. A. Abd El-Latif, "Efficient Brain Tumor Detection with Lightweight End-to-End Deep Learning Model," *Cancers*, vol.15, no.10, May 2023. Article(CrossRefLink)

[21] D. H. Mahlool and M. H. Abed, "Distributed brain tumor diagnosis using a federated learning environment," *Bulletin of Electrical Engineering and Informatics*, vol.11, no.6, pp.3313-3321, Dec. 2022. Article(CrossRefLink)

[22] W. Li et al., "Privacy-preserving Federated Brain Tumour Segmentation," in *Proc. of Machine Learning in Medical Imaging: 10th International Workshop, MLMI 2019*, pp.133-141, Oct. 2019. Article(CrossRefLink)

[23] V. Nair and G. E. Hinton, "Rectified Linear Units Improve Restricted Boltzmann Machines," in *Proc. of ICML'10: Proceedings of the 27th International Conference on International Conference on Machine Learning*, pp.807-814, 2010. Article(CrossRefLink)

[24] A. Mao, M. Mohri, and Y. Zhong, "Cross-Entropy Loss Functions: Theoretical Analysis and Applications," in *Proc. of ICML'23: Proceedings of the 40th International Conference on Machine Learning*, pp.23803-23828, 2023. Article(CrossRefLink)

[25] D. P. Kingma and J. Ba, "Adam: A Method for Stochastic Optimization," in *Proc. of 3rd International Conference for Learning Representations*, 2015. Article(CrossRefLink)

[26] M. Nagabushanam, S. Jeevanandham, S. Ramalingam, K. Baskaran, and A. Maheshwari, "AI based E-ATM Security and Surveillance System using BLYNK-loT Server," in *Proc. of the 2022 3rd International Conference on Communication, Computing and Industry 4.0 (C2I4)*, pp.1-5, 2022. Article(CrossRefLink)

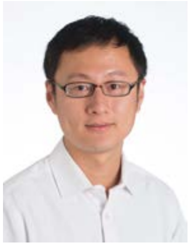
[27] J. Lu, "AdaSmooth: An Adaptive Learning Rate Method based on Effective Ratio," in *Proc. of Sentiment Analysis and Deep Learning: Proceedings of ICSADL 2022*, pp.273-293, Jan. 2023. Article(CrossRefLink)

[28] A. Selvapandian and K. Manivannan, "Fusion based Glioma brain tumor detection and segmentation using ANFIS classification," *Computer Methods and Programs in Biomedicine*, vol.166, pp.33-38, Nov. 2018. Article(CrossRefLink)

[29] M. Sajjad, S. Khan, K. Muhammad, W. Wu, A. Ullah, and S. W. Baik, "Multi-grade brain tumor classification using deep CNN with extensive data augmentation," *Journal of Computational Science*, vol.30, pp.174-182, Jan. 2019. Article(CrossRefLink)
[30] V. V. S. Sasank and S. Venkateswarlu, "Hybrid deep neural network with adaptive rain optimizer algorithm for multi-grade brain tumor classification of MRI images," *Multimedia Tools and Applications*, vol.81, no.6, pp.8021-8057, Mar. 2022. Article(CrossRefLink)
[31] A. Kabir Anaraki, M. Ayati, and F. Kazemi, "Magnetic resonance imaging-based brain tumor grades classification and grading via convolutional neural networks and genetic algorithms," *Biocybernetics and Biomedical Engineering*, vol.39, no.1, pp.63-74, Jan.-Mar. 2019. Article(CrossRefLink)
[32] N. Noreen, S. Palaniappan, A. Qayyum, I. Ahmad, M. Imran, and M. Shoaib, "A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor," *IEEE Access*, vol.8, pp.55135-55144, 2020. Article(CrossRefLink)
[33] A. Gurunathan and B. Krishnan, "A Hybrid CNN-GLCM Classifier For Detection And Grade Classification Of Brain Tumor," *Brain Imaging and Behavior*, vol.16, no.3, pp.1410-1427, Jun. 2022. Article(CrossRefLink)
[34] A. A. Funmilola et al., "Fuzzy k-c-means Clustering Algorithm for Medical Image Segmentation," *Journal of Information Engineering and Applications*, vol.2, no.6, 2012. Article(CrossRefLink)

**Abdul Raheem** is currently doing his Ph.D. at the Beijing University of Technology, Beijing, China. In 2019 did M.S. in Mechanical Engineering (Automation research direction) from the Beijing Institute of graphic communication, Beijing, China. His research interests primarily focus on various domains of Machine Learning, federated learning, data privacy, and medical image segmentation.

**Zhen Yang** (Member, IEEE) received the Ph.D. degree in signal processing from the Beijing University of Posts and Telecommunications, China. He is currently the Full Professor of computer science and engineering with the Beijing University of Technology, Beijing, China. He has authored or coauthored more than 30 papers in highly ranked journals and top conference proceedings. His research interests include data mining, machine learning, trusted computing, and content security. He is the Senior Member of the Chinese Institute of Electronics.



**Haiyang Yu** received the PhD degree in computer science and technology from Beijing University of Technology in 2019. From 2017 to 2018, he visited the University of Melbourne in Australia. He is currently an associate professor of computer science at Beijing University of Technology. His research interests include cloud storage auditing and blockchain.

**Dr. Muhammad Yaqub** is advancing his career as a Postdoctoral Researcher at Hunan University, continuing to explore and innovate within his areas of expertise. An esteemed graduate of Beijing University of Technology, P.R. China, he completed his doctoral studies in Engineering (Electronic Science and Technology) in 2023. His academic journey, which began with completing both his Master's and Bachelor's degrees at COMSATS University Islamabad, the top-ranked university in Pakistan. With research interests spanning medical image processing, computer vision, artificial intelligence, machine learning, and data science, Dr. Yaqub has authored and co-authored over 25 research publications in well-reputed international journals, marking significant contributions to his field.

**Fahad Sabah** is a senior lecturer at Faculty of CS&IT, Superior University, Pakistan. He is currently pursuing the Ph.D. degree in Computer Science with the Faculty of Information Technology, Beijing University of Technology, China. His research interests include Machine Learning, federated learning, with special focus on personalization via meta-learning, and real world computer applications.

**Mr. Shahzad Ahmed** earned his Bachelor of Science degree in Computer Science from COMSATS University Islamabad, Pakistan in 2015, where he also completed his Master's degree in the same field in 2017. Currently, he is pursuing a Ph.D. in Electronic Science and Technology at Beijing University of Technology, China. His research interests span across Deep Learning, Big Data, and medical imaging, with a particular emphasis on developing cutting-edge solutions for medical image analysis and processing.

**Malik A. Manan** is a Ph.D. Scholar at Beijing University of Technology in China, where he is in the third year of his studies and set to graduate in June 2024. He has a background in Electrical and computer Engineering and has researched and worked on various scientific projects such as medical imaging for disease detection and segmentation. He has also worked as a head of department at Riphah International college affiliated with GCU Faisalabad, in Dera Ghazi Khan, Pakistan and as a research assistant at COMSATS University in Islamabad, Pakistan. His research interests include machine learning, image processing, and medical data science.

**Dr. Imran Shabir Chuhan** received his Ph.D. degree in Mathematics from the Beijing University of Technology (BJUT), China. From 2015 to Present, he worked as a Lecturer with the Department of mathematics, UoKAJK, Pakistan. His research interest includes Machine Learning, Mathematical modeling, Simulation Analysis. Mr. Imran awards and honors include the China Scholarship Council (CSC, China), and the star contribution award for best researcher 2021 (Beijing University of Technology, China). Moreover, he has published many papers in reputed journals and conferences.