

Lecture Notes in Networks and Systems 1440

Xin-She Yang
R. Simon Sherratt
Nilanjan Dey
Amit Joshi *Editors*

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Editors

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Preface

The Tenth International Congress on Information and Communication Technology will be held during 18–21 February 2025 in a hybrid mode, Physical at London, UK and Digital Platform: Zoom. ICICT 2025 organised by Global Knowledge Research Foundation and Managed by G R Scholastic LLP. The associated partners were Springer and Springer Nature. The conference will provide a useful and wide platform both for display of the latest research and for exchange of research results and thoughts. The participants of the conference will be from almost every part of the world, with backgrounds of either academia or industry, allowing a real multinational multicultural exchange of experiences and ideas.

A great pool of more than 2200 papers were received for this conference from across 115 countries among which around 433 papers were accepted and will be presented physically at London and digital platform Zoom during the four days. Due to the overwhelming response, we had to drop many papers in the hierarchy of the quality. Total 65 technical sessions will be organised in parallel in 4 days along with a few keynotes and panel discussions in hybrid mode. The conference will be involved in deep discussion and issues which will be intended to solve at global levels. New technologies will be proposed, experiences will be shared, and future solutions for design infrastructure for ICT will also be discussed. The final papers will be published in ten volumes of proceedings by Springer LNNS Series. Over the years, this congress has been organised and conceptualised with collective efforts of a large number of individuals. I would like to thank each of the committee members and the reviewers for their excellent work in reviewing the papers. Grateful acknowledgements are extended to the team of Global Knowledge Research Foundation for their valuable efforts and support.

I look forward to welcoming you to the 11th Edition of this ICICT Congress 2026.

London, UK
England, UK
Kolkata, India
Ahmedabad, India

Xin-She Yang
R. Simon Sherratt
Nilanjan Dey
Amit Joshi

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About the Editors

Xin-She Yang obtained his D.Phil. in Applied Mathematics from the University of Oxford. He then worked at Cambridge University and then later at the National Physical Laboratory (UK) as Senior Research Scientist. Now he is Reader at Middlesex University London, and Co-editor of the *Springer Tracts in Nature-Inspired Computing*. He is also an elected Fellow of the Institute of Mathematics and its Applications (FIMA), UK. He was the IEEE Computational Intelligence Society (CIS) chair for the Task Force on Business Intelligence and Knowledge Management (2015–2020). He has published more than 50 books and more than 400 peer-reviewed research papers with more than 90,000 citations, and he has been on the prestigious list of most influential researchers or highly cited researchers (Web of Sciences) every year since 2016.

R. Simon Sherratt was born near Liverpool, England, in 1969. He is currently Professor of Biosensors at the Department of Biomedical Engineering, University of Reading, UK. His main research area is signal processing and personal communications in consumer devices, focusing on wearable devices and health care. Professor Sherratt received the 1st place IEEE Chester Sall Memorial Award in 2006, the 2nd place in 2016, and the 3rd place in 2017.

Nilanjan Dey is an associate professor in the Department of Computer Science and Engineering, Techno International New Town, Kolkata, India. He is a visiting fellow of the University of Reading, UK. He also holds a position of Adjunct Professor at Ton Duc Thang University, Ho Chi Minh City, Vietnam. Previously, he held an honorary position of Visiting Scientist at Global Biomedical Technologies Inc., CA, USA (2012–2015). He was awarded his Ph.D. from Jadavpur University in 2015. He is Editor-in-Chief of the *International Journal of Ambient Computing and Intelligence*, IGI Global, USA. He is Series Co-editor of *Springer Tracts in Nature-Inspired Computing* (Springer Nature), *Data-Intensive Research* (Springer Nature), and *Advances in Ubiquitous Sensing Applications for Healthcare* (Elsevier). He is an associate editor of *IET Image Processing* and an editorial board member of *Complex and Intelligent Systems*, Springer Nature, *Applied Soft Computing*, Elsevier, etc. He

is having 35 authored books and over 300 publications in medical imaging, machine learning, computer-aided diagnosis, data mining, etc. He is Fellow of IETE and Senior Member of IEEE.

Amit Joshi is currently serving as the director of the esteemed Global Knowledge Research Foundation, India, this distinguished individual is an accomplished entrepreneur and researcher. His academic journey includes obtaining a B.Tech. degree in Information Technology, an M.Tech., in Computer Science and Engineering, and a Ph.D. focusing on the intricate fields of Cloud Computing and Cryptography in Medical Imaging, experiencing his vision with his rich experience spanning approximately 15 years and realising the need of globalisation in education and business. His present-day interests are primarily oriented towards the critical examination of government strategies and global forum requirements across education and business sectors. His active affiliations include esteemed professional societies such as ACM, IEEE, CSI, AMIE, IACSIT-Singapore, IDES, ACEEE, NPA, and more. His past responsibilities have included chairing the Computer Society of India (CSI) Udaipur Chapter and serving as Secretary and Chairman for the Association of Computing Machinery (ACM) Udaipur Professional Chapter. He was also the International Young ICT Chair for International Federation for Information Processing (IFIP), Austria formed through UNESCO in 1960. He has presented and authored over 50 papers in reputable national and international journals and conferences, specifically those organised by IEEE and ACM. His editorial contributions include editing over 100 books published by renowned publishers such as Springer, T&F, and ACM. He has also organised over 100 national and international conference delegations and workshops in over 20 countries including the USA, Canada, major of Europe, Southeast Asia through various societies, and international organisations. Apart from his academic pursuits, he is also actively involved in the global business and industrial community. He serves as the director of the Knowledge Chamber of Commerce and Industry, where he concentrates on establishing effective relationships among bureaucrats, industry associations, academic leaders, and regulatory authorities to address common research-related issues across sectors. He has organised over 50 industry forum events, facilitating communication with state and federal establishments, as well as corporate and academic bodies, to promote collaboration between industry and government sectors. Also, he has attended various high-profile events at UNESCO, International Telecommunication Union (ITU), Geneva, and with various embassies, consulates, and federal governments. Also, one of his primary focuses also is on building academic collaborations and promoting the 'ZAPAL' initiative, a future-oriented project involving abroad education powered by his profit venture, G R Scholastic LLP. Overall, he is a forward-thinking individual who is dedicated to creating networks across various sectors, particularly in education and industry.

BrainDetective: An Advanced Deep Learning Application for Early Detection, Segmentation and Classification of Brain Tumours Using MRI Images



Nazlı Tokatlı, Mücahit Bayram, Hatice Ogur, Yusuf Kılıç, Vesile Han, Kutay Can Batur, and Halis Altun

Abstract This study aims to create deep learning models for the early identification and classification of brain tumours. Models like U-Net, DAU-Net, DAU-Net 3D, and SGANet have been used to evaluate brain MRI images accurately. Magnetic resonance imaging (MRI) is the most commonly used method in brain tumour diagnosis, but it is a complicated procedure due to the brain's complex structure. This study looked into the ability of deep learning architectures to increase the accuracy of brain tumour diagnosis. We used the BraTS 2020 dataset to segment and classify brain tumours. The U-Net model designed for the project achieved an accuracy rate of 97% with a loss of 47%, DAU-Net reached 90% accuracy with a loss of 33%, DAU-Net 3D achieved 99% accuracy with a loss of 35%, and SGANet achieved 99% accuracy with a loss of 20%, all demonstrating effective outcomes. These findings aim to improve patient care quality by speeding up medical diagnosis processes using computer-aided technology. Doctors can detect 3D tumours from MRI pictures using software developed as part of the research. The work packages correctly handled project management throughout the study's data collection, model creation, and

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evaluation stages. Regarding brain tumour segmentation, 3D U-Net architecture with multi-head attention mechanisms provides doctors with the best tools for planning surgery and giving each patient the best treatment options. The user-friendly Turkish interface enables simple MRI picture uploads and quick, understandable findings.

Keywords 3D brain tumour diagnosis · Deep learning models · MR imaging · AI applications in Turkish health system

1 Introduction

This study's scientific value comes from applying deep learning and computer-aided systems for the early detection and classification of brain cancers. According to the latest World Health Organization data, brain tumours are among the most common causes of cancer death globally and may develop at any age [1]. They are most fatal to those under the age of 40. Early diagnosis of brain tumours dramatically improves patient survival and treatment success. Rapid and precise picture assessment is critical; however, manual evaluations are time-consuming and prone to errors. As a result, artificial intelligence applications have become prevalent in techniques such as computed tomography (CT) and magnetic resonance (MR) [2]. The latest developments in deep learning and machine learning have significantly improved pattern identification in biological images [3]. These innovative approaches meet the needs of automated medical decision-making systems because human processes are expensive to accomplish, labour-intensive, and prone to errors [4].

In the present research, a multi-model approach developed with deep learning and machine learning algorithms outperformed existing methods for detecting and classifying brain cancers in terms of accuracy and efficiency. The BraTS 2020 dataset was crucial in training and testing these algorithms. This dataset contains a large amount of data for finding and categorizing cancers in brain MR images. Advanced deep learning models were utilized to speed up and improve brain tumour diagnosis accuracy in these MRI scans. Modern deep learning structures such as U-Net, DAU-Net, DAU-Net 3D, and SGANet were used to analyse brain MRI scans. Each model's performance was evaluated by achieving high accuracy rates and low loss values while segmenting and classifying brain tumours. A user-friendly interface was created to upload MR images and retrieve quick conclusions. The application's effectiveness was increased through case studies and testing procedures. This research is essential for precisely identifying the spatial extent and positioning of brain tumours using 3D brain models generated by MRI scans, which is required for brain telemetry device placement and surgical planning. The literature indicates that machine learning and deep learning algorithms are helpful in the diagnosis of brain tumours [5–11]. However, there are places where these procedures might be increased for more precise and effective results. This study is planned to improve brain tumour detection by filling the gaps in the literature. Furthermore, segmenting brain tumours will improve surgical planning by preserving essential structures surrounding the tumour.

The study's contributions include early diagnosis, obtaining a 3D image of the brain, convenience in brain telemetry and neurosurgical applications, a user-friendly Turkish interface, and developing a clinical decision support system via the application. The study's sections cover related work, research methodology, data preparation, model designs, and findings. The results section presents the findings, and the conclusions section interprets the findings to conclude the study.

2 Related Work

The diagnosis and classification of brain tumours have been a topic of extensive research and experimentation in the field of medical imaging for many years. These studies recommend using various algorithms and deep learning methods to analyse brain MRI images.

DAU-Net is a model that incorporates attention mechanisms along with U-Net. It is particularly effective in capturing detailed features in medical images. Introduced by Zhang et al., DAU-Net provides more detailed and precise segmentation results due to its attention mechanisms. This feature has made DAU-Net one of the models used in this project for distinguishing various types of brain tumours [12].

3D DAU-Net is a model optimized for volumetric data analysis and capable of working with 3D medical images. Developed by Zhao et al., this model offers high accuracy and reliability in 3D analysis of brain MRI images. Its 3D tumour segmentation and classification capability has made it a significant component of the project [13].

SGANet is a model that combines generative adversarial networks (GANs) with U-Net. Proposed by Yu et al., this model has proven effective in improving the quality of medical images and achieving better results in segmentation tasks. The high performance of SGANet plays a crucial role in this project's segmentation and classification of brain tumours [14].

Recent studies have examined deep learning techniques for brain tumour detection, segmentation, and classification using MRI images. Various models have been proposed in this field, such as U-Net [15] for segmentation and CNN [16] for classification. Advanced approaches like YOLOv5 and FastAi have yielded promising results with accuracy rates of 85.95% and 95.78%, respectively [17]. A custom Mask R-CNN model with a DenseNet-41 backbone demonstrated high accuracy in both segmentation (96.3%) and classification (98.34%) tasks [18]. Transfer learning techniques like AlexNet CNN have achieved an impressive accuracy rate of 99.62% [19]. Multi-task classification studies using CNN have also been explored for various tumour classification tasks [20]. Additionally, 3D-U-Net models have been used for volumetric segmentation, followed by CNN-based classification [21]. These advancements aim to improve the early detection and diagnosis of brain tumours.

3 Proposed Design

The proposed system aims to analyse brain MRI images using deep learning models. This system offers an innovative approach to brain tumour segmentation and detection by leveraging the BraTS 2020 dataset. The system utilizes a comprehensive database consisting of T1, seg, T1ce, T2, and FLAIR modalities to accurately detect brain tumour types in both 3D and 2D. The BraTS 2020 dataset consists of a total of 369 patients, with each patient having five .nii files: flair.nii, t1.nii, t1ce.nii, t2.nii, and seg.nii, which contains the 3D-labelled tumour. Additionally, a .csv file provides information on whether the tumour is benign or malignant, along with another .csv file containing data such as the patient's age, whether the tumour was removed, and survival time. During model training, these data were processed and converted into .npy and .tfRecord formats. The dataset is divided into two main categories: HGG (High-Grade Glioma) and LGG (Low-Grade Glioma). With augmentation techniques, the dataset size was increased to over 100,000 samples. However, the BraTS 2020 dataset has significant limitations, such as the absence of important clinical variables (volume, gender, histopathological data) and tumour subtypes. These limitations may restrict the model's application in real-world scenarios. In the study, these limitations were considered, with a focus on the generalizability of the findings. To enhance applicability across a broader clinical range, the use of various datasets, along with techniques like transfer learning or domain adaptation, can enable the model to adapt to different data sources. The project's software architecture is designed to be modular and scalable, with each model developed as an independent module and integrated into the application. The system architecture is shown in Fig. 1.

3.1 Data Processing

Data processing workflows were based on the Factory and Strategy design patterns. The Factory pattern defines preprocessing stages across numerous modalities, whilst the Strategy style allows for the dynamic deployment of data augmentation approaches [22, 23]. These approaches ensure that data preparation operations are both flexible and efficient. Initially, the system meticulously processes each modality to improve data quality. Modality-based directories are built, and axis corrections and channel placements are performed. Normalization is carried out utilizing Z-score and Min-Max approaches. This allows the model to be trained using consistent, high-quality data. Data augmentation techniques are subsequently applied to improve the model's generalization capability, and the processed data is stored in NumPy arrays and TFRecord format for easy access and processing. This approach ensures that the data is displayed effectively. Figure 2 displays the data processing and storage procedures.

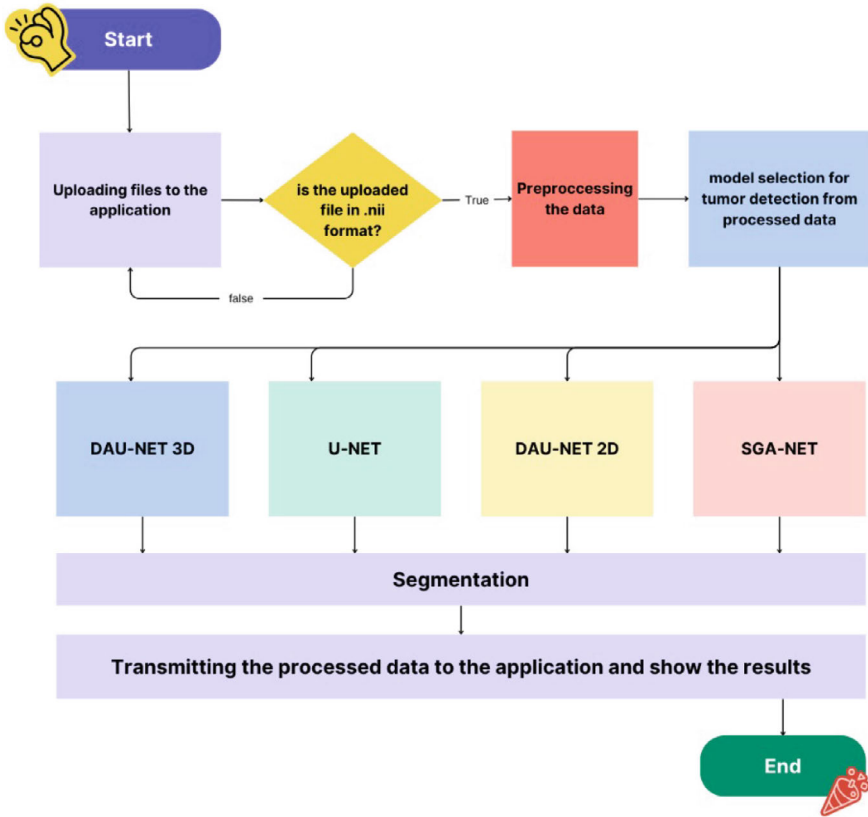


Fig. 1 General design stages of the application

3.2 Model Development

The project focuses on deep learning architectures such as DAUNet, DAUNet 3D, U-Net, and SGANet. Each model is evaluated and improved based on existing approaches in the literature, optimizing their segmentation capabilities. These models aim to achieve high accuracy rates while minimizing the risk of over-fitting. Figure 3 explains the step-by-step process of the model development and improvement.

4 Experimental Methodology

In the experimental phase of the project, U-Net, DAU-Net, DAU-Net 3D, and SGANet models were trained with the BraTS 2020 dataset, and the hyperparameter

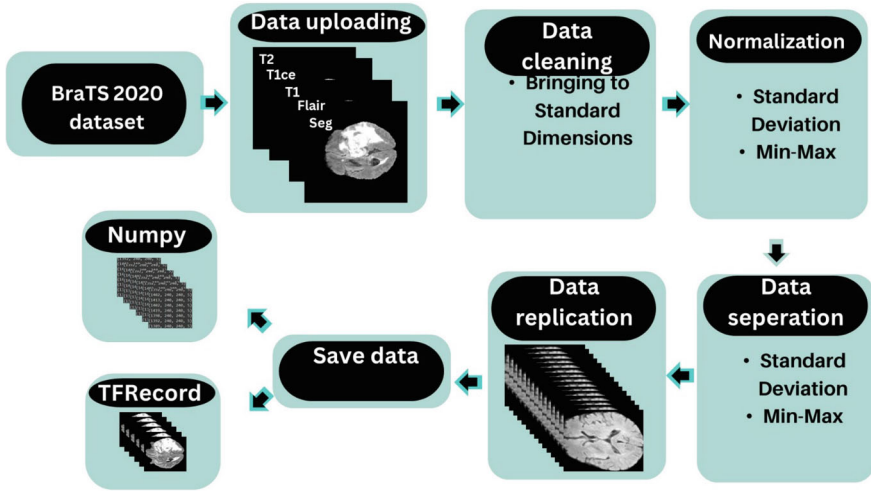


Fig. 2 Data preparation process of the application

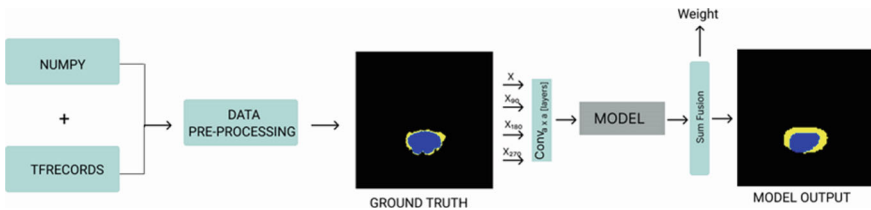


Fig. 3 Processing stages of models

settings of each model were carefully optimized. Throughout the training process, the performance of each model was evaluated based on accuracy rates and loss values.

4.1 Data Preparation and Preprocessing Process

In the experimental phase of the project, U-Net, DAU-Net, DAU-Net 3D, and SGANet models were trained with the BraTS 2020 dataset, and the hyperparameter settings of each model were carefully optimized. Throughout the training process, the performance of each model was evaluated based on accuracy rates and loss values [24, 25].

During the preparation phase, directories were established for each patient in the dataset, and data use and access were streamlined by categorizing directories by modality type. The modes in the files, which contained axis corrections and channel placements, were loaded and processed appropriately. Data was normalized using standardization (Z-score) and min-max normalization methods, with clipping

operations used to limit the influence of outliers [26]. Data augmentation techniques such as rotation, shifting, cropping, and mirroring were used further to develop the model's generalization capabilities [27]. Processed data was saved as NumPy arrays (.npy format) for quick access and then translated to TensorFlow's TFRecord format. The TFRecord format was created for efficient processing of big datasets, and the data was serialized and saved in this format for use in training and testing [28, 29].

4.2 *U-Net*

The U-Net layout is a highly effective structure for brain tumour segmentation and biomedical imaging. It uses an autoencoder-like structure to process the input image via encoding and decoding routes. While the encoding path collects contextual information, the decoding path preserves details and returns the image to its original size [30, 31]. U-Net has shown outstanding performance, particularly in the precise identification of brain tumours, with high accuracy even with fragile datasets [32–34].

4.3 *DAUNet 3D*

The DAUNet 3D model uses attention mechanisms and deep learning techniques to achieve remarkable precision in brain tumour segmentation. Attention procedures increase segmentation accuracy by detecting key regions, but deep learning systems may learn complicated structures and fine details. 3D convolutional layers maintain the three-dimensional structure of brain images, allowing for more detailed analysis. Incremental learning techniques incorporate segmentation findings at many levels, improving overall accuracy. DAUNet 3D is a valuable tool for medical imaging applications that require volumetric analysis, and it performs excellently.

4.4 *DAUNet*

DAUNet and DAUNet 3D models can be helpful for medical image segmentation. DAUNet works with 2D slice data, but DAUNet 3D handles 3D volume data. DAUNet uses 2D convolutional, max pooling, and upsampling layers to improve accuracy using attention methods. Generalized Dice Loss and Categorical Crossentropy are utilized as loss functions. During the training phase, the model's performance was measured using metrics such as the Dice coefficient, sensitivity, and specificity, and the training process was shown. The model produced effective results for brain tumour segmentation.

4.5 SGANet

SGANet is a deep learning model that provides excellent accuracy and precision in medical image segmentation. It improves segmentation problems by integrating Generative Adversarial Networks (GAN) and U-Net architectures [35, 36]. The model employs a U-Net-like generator network to turn images into segmentation masks and a discriminator network to evaluate the masks' realism [37, 38]. The adversarial training technique improves segmentation accuracy through competition [39]. SGANet provides effective results in medical applications, such as the exact segmentation of brain tumours, and has demonstrated effectiveness in this study [40].

In this study, the models were not combined. Instead, the application includes four distinct models capable of detecting tumours in both 3D and 2D, allowing the user to select the desired model. The developed interface currently operates with the 3D DAU-Net model, which has demonstrated the highest performance. The comparison of multiple models was conducted to evaluate the performance of different models on the same dataset and to assess each model's effectiveness in solving specific problems. Although this approach is rare in the literature, it is crucial for selecting the best-performing model or testing whether the integration of models provides new solutions. In future stages, the integration of other models used in the study is planned. The joint evaluation of the models aims to identify the strengths and weaknesses of various model architectures and develop solutions that are better suited to clinical applications. As shown in Table 1, the comparison criteria include performance metrics, which allowed us to objectively assess the models' segmentation success and overall performance. The attention mechanisms and multi-scale feature extraction capabilities of SGANet and DAU-Net enhanced their segmentation and classification performance. These models demonstrated higher accuracy and lower loss rates compared to others (Fig. 4).

Table 1 Performance metrics of models

Model	Dice coefficient	Sensitivity	Specificity
DAU-Net	[0.9798, 0.8940, 0.8950]	[0.9846, 0.8878, 0.8780]	[0.9995, 0.9991, 0.9970]
3D DAU-Net	[0.9798, 0.8940, 0.8950]	[0.9846, 0.8878, 0.8780]	[0.9995, 0.9991, 0.9970]
SGANet	[0.9700, 0.9725, 0.9610]	[0.9846, 0.8878, 0.8780]	[0.9995, 0.9991, 0.9970]
U-Net	[0.9826, 0.9753, 1.0]	[0.9894, 0.9891, 1.0]	[0.9986, 0.9969, 1.0]

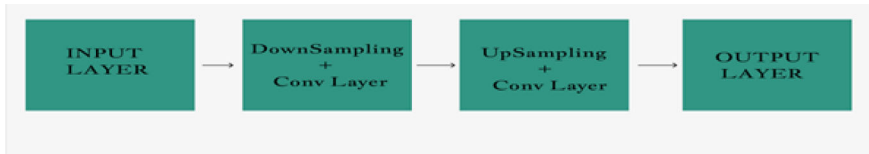


Fig. 4 General models and layers

5 Experiment Results

In conclusion, the developed models have demonstrated high accuracy rates and effective performance. Important metrics such as Dice Coefficient, Sensitivity (Recall), and Specificity were used to evaluate model performance. These metrics are commonly used to measure how close the model's segmentation results are to the ground truth and their accuracy. The Dice Coefficient, Sensitivity, and Specificity calculations for the developed models were performed using the following formulas:

$$\text{Dice Katsayısı} = \frac{2 \times \text{TP}}{2 \times \text{TP} + \text{FP} + \text{FN}} \quad (1)$$

$$\text{Duyarlılık (Recall)} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (2)$$

$$\text{Özgüllük (Specificity)} = \frac{\text{TN}}{\text{TN} + \text{FP}} \quad (3)$$

6 Discussion

In recent years, significant progress has been made in using deep learning models for the detection and classification of brain tumours. This study presents a rare approach in the literature by integrating U-Net, DAU-Net, DAU-Net 3D, and SGANet models into a single platform, enabling the comparative evaluation of different models and techniques. In particular, the DAU-Net and SGANet models demonstrated superior performance due to their attention mechanisms and multi-scale feature extraction capabilities. One of the primary reasons for the observed loss rate is the class imbalance in the BraTS 2020 dataset. In this study, 3D MRI images in .nii format were utilized. During the data preprocessing phase, the five .nii files obtained for each patient from the BraTS 2020 dataset were converted into .npy or .tfRecord formats. Subsequently, these data were segmented into 155 slices per patient. After the slicing process, random data augmentation techniques were applied. However, including brain regions without tumours in this process led to the model's insufficient learning

of rare tumour classes. This issue may result in incorrect outcomes during tumour segmentation (Fig. 5).

To mitigate the effects of this issue, improvements can be made during the model training phase, particularly in custom layers and preprocessing steps, taking class imbalance into account. Specifically, implementing oversampling for rare classes or undersampling for the majority class can improve the representation of rare classes, and advanced data augmentation techniques can enhance the overall performance of the model. The DAU-Net model, due to its attention-based architecture, achieved high success in brain tumour segmentation across metrics such as Dice coefficient, sensitivity, and specificity.

On the other hand, the SGANet model achieved a 99% accuracy rate due to its enhanced generalization capacity, which was obtained through the use of ResNet blocks, Guided Attention Blocks, and the GaussianNoise layer. The integration of these four models into a single platform allowed for a comprehensive evaluation of their strengths and made a significant contribution to the literature. The user-friendly interface developed in the study enables healthcare professionals to quickly and accurately analyse MRI data. Additionally, offering the interface in Turkish provides localized benefits, enhancing accessibility within the Turkish healthcare system. The



Fig. 5 Performance of models

study has some limitations, particularly regarding the size and diversity of the BraTS 2020 dataset, which may affect the generalizability of the findings. Future studies will use larger datasets, obtain the necessary ethical approvals from public hospitals in Turkey, and conduct large-scale clinical trials to increase the reliability of the results. In conclusion, this study demonstrates the potential of deep learning-based systems in medical image analysis and highlights the importance of these systems in clinical applications. These systems are particularly valuable in reducing the workload of doctors and alleviating the impact of the shortage of neurologists in public hospitals in Turkey. Further research supported by large datasets and clinical trials could enhance the effectiveness and applicability of these models even more.

7 Future Work

The developed Turkish interface and 3D imaging capabilities are expected to provide significant contributions in terms of accessibility and ease of use within the Turkish healthcare system. How the interface will be tested in practice and how user feedback will be collected are critical points for evaluating the software's effectiveness. In future stages, pilot studies are planned to assess the software's applicability in healthcare institutions. These studies will aim to ensure compatibility with international health standards such as Health Level Seven (HL7) and Digital Imaging and Communications in Medicine (DICOM), enabling smooth integration of the software with existing hospital information management systems. Comprehensive tests will be conducted in partnership with healthcare institutions affiliated with our university to evaluate to what extent the software reduces the workload of doctors in clinical settings. Thanks to its automatic 3D imaging and analysis features, the software is expected to significantly reduce doctors' workloads by speeding up diagnostic processes compared to manual methods. The results of these tests will demonstrate how well the software aligns with its goals while providing valuable feedback to optimize clinical integration. Additionally, for economically disadvantaged citizens, the software aims to contribute by reducing the number of tests needed for tumour detection, thus enabling access to healthcare services without financial concerns. Images of the current interface of the project can be found in Figs. 6 and 7.

8 Conclusion

In this research, brain tumours were quickly and accurately diagnosed using deep learning-based models. There is a chance that this system will raise the standard of healthcare. Deep learning techniques help in the early detection of brain tumours, which makes early and efficient treatments possible. Furthermore, the program and user interface that have been developed are user-friendly, allowing for 3D imaging

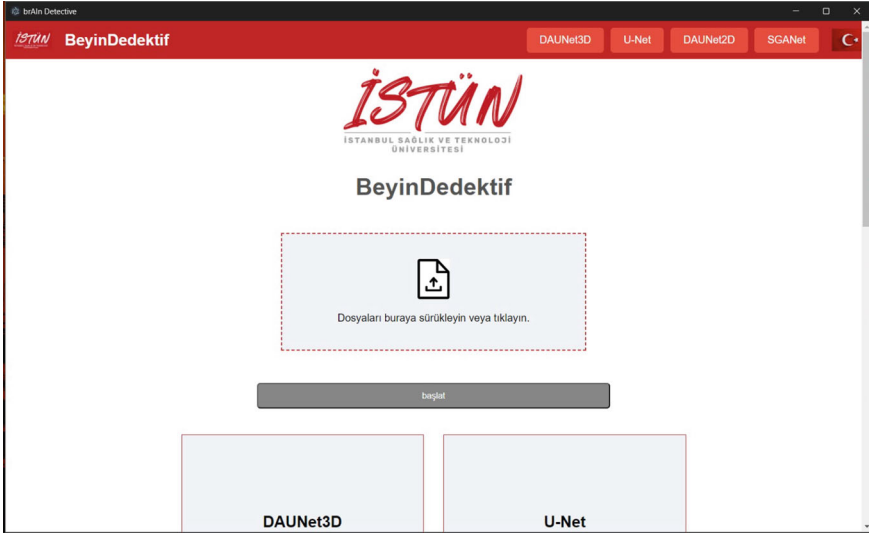


Fig. 6 Application interface

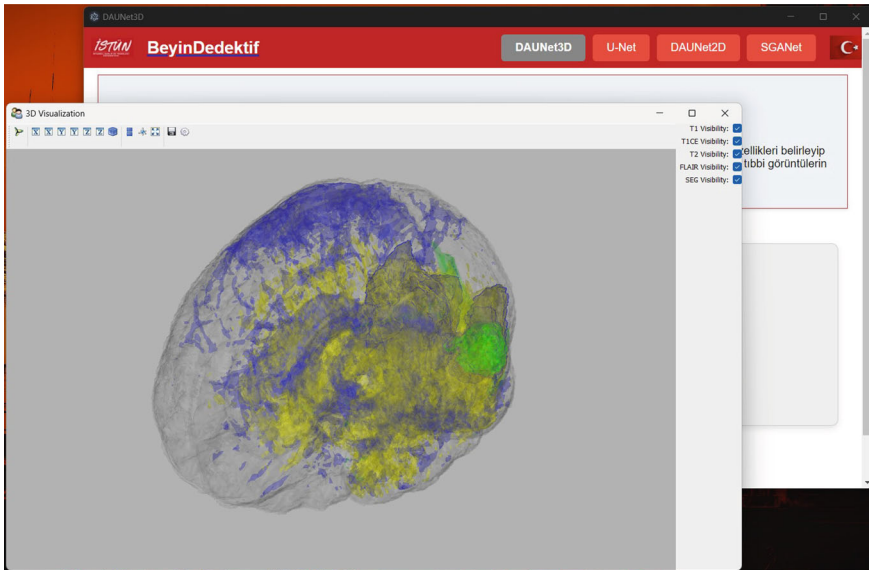


Fig. 7 3D tumour detection in practice

and extensive analysis of the brain and tumours. This information is useful for clinical evaluations and helps with treatment planning. The study has demonstrated the effectiveness of deep learning techniques in medical image analysis and has contributed to the proliferation of artificial intelligence applications in healthcare. This

project highlights the potential of artificial intelligence in the healthcare sector, forming a crucial foundation for future research and clinical applications. The broader application of deep learning-based systems in healthcare will improve patient care and make medical diagnosis processes more effective.

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32. This architecture has several applications ranging from consumer videos, earth observations, and medical imaging (2020)
33. The encoder path of U-Net captures the context of the input image, this path is simply a pipeline of convolutional and pooling layers (2020)
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