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Deepfake Detection in Medical Images

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ABSTRACT: Deepfakes in medical imaging pose a critical threat to healthcare integrity by enabling malicious alterations of diagnostic scans. In this paper, we propose a novel approach to detect deepfake modifications in brain MRI images using Mask R-CNN. Our system distinguishes among four categories (i) real tumor, (ii) no tumor, (iii) deepfake-added tumor, and (iv) deepfake-removed tumor by leveraging a pixel-level segmentation methodology. This solution addresses the challenge of subtle manipulations, often imperceptible to the naked eye, by combining instance segmentation and classification, thereby offering higher diagnostic reliability. We begin by reviewing existing work on object detection, segmentation, and deepfake detection in medical images. Our proposed system architecture integrates a Next.js front end with a Python-based backend, featuring a Mask R-CNN model trained on a curated dataset of 1300 brain MRI scans. Experimental results demonstrate that our approach can effectively identify tampered regions, enhancing trust in medical imaging and mitigating the risk of fraudulent manipulations. We conclude with a discussion of future directions for improving model generalizability and performance in broader clinical contexts.

KEYWORDS: Deepfake Detection, Medical Imaging, Brain MRI, Mask R-CNN, Segmentation, Tumor Analysis

I. INTRODUCTION

Medical images, such as MRI scans, are a cornerstone of modern healthcare diagnostics. These images guide clinical decision-making, influence treatment plans, and play a pivotal role in research studies. However, the emergence of advanced image synthesis and manipulation techniques—commonly referred to as deepfakes poses a new threat to the integrity and reliability of medical data. Malicious actors can insert or remove pathological markers, such as tumors, in MRI scans, potentially leading to misdiagnosis or fraud.

Historically, digital image manipulation required extensive manual editing skills. With the rise of deep generative models like Generative Adversarial Networks (GANs), the process of creating high-fidelity synthetic or tampered images has become more accessible and difficult to detect. This phenomenon has been widely studied in the context of facial manipulations in videos and photographs, but its implications in the medical domain have only recently garnered attention.

Brain MRI images are especially susceptible to deepfake manipulations because they are rich in intricate anatomical details. A slight alteration to an MRI such as adding a small tumor mass could be overlooked by automated or semi-automated screening systems. Conversely, removing a legitimate tumor from a scan might lead to severe clinical misinterpretations. Robust, automated detection systems are therefore necessary to ensure that tampered images do not compromise patient care.

Modern object detection architectures like YOLO and Faster R-CNN have been instrumental in medical image analysis tasks, including tumor detection, lesion segmentation, and anomaly classification. However, these methods typically provide only bounding boxes and lack the fine-grained pixel-level segmentation required to spot subtle manipulations. Mask R-CNN improves upon these models by offering instance segmentation, which can delineate the exact shape of a suspicious region making it particularly suitable for detecting artificially added or removed tumors.In this paper, we propose a comprehensive solution to detect deepfakes in brain MRI images by leveraging Mask R-

CNN. Our system is designed to handle four categories: real tumor, no tumor, deepfake-added tumor, and deepfake-removed tumor. We integrate this model into a user-friendly Next.js front end, ensuring seamless interaction for medical professionals or system administrators. We also discuss our training process, dataset composition, system

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architecture, and evaluation metrics. Finally, we present experimental results and outline future directions for expanding this approach to other types of medical imaging and broader clinical applications.

The remainder of this paper is organized as follows. We first provide a thorough literature review of relevant works in deepfake detection, medical image segmentation, and Mask R-CNN applications. Next, we describe the proposed system, including the software and hardware requirements. We then outline the detailed methodology, covering the architecture, modules, and development approach. Following this, we present the results and discuss the system's performance. We conclude with a comprehensive discussion of our findings and outline future research directions. Finally, the paper ends with a list of references.

II. LITERATURE REVIEW

[1] MEHMET KARAKÖSE, HASAN YETİŞ , AND MERT ÇEÇEN (Mask R-CNN):
The paper "A New Approach for Effective Medical Deepfake Detection in Medical Images" by Mehmet Karaköse, Hasan Yetiş, and Mert Çeçen addresses the growing threat of deepfake manipulations in medical imaging, where realistic fake scans can lead to misdiagnosis, treatment errors, or fraud. The authors review existing methods such as U-Net, Sparse CNNs, and physiological signal estimation techniques, noting their limitations in terms of accuracy and efficiency, especially in clinical settings. They emphasize the challenge of detecting subtle alterations in standardized medical images and the scarcity of labeled data for training deep learning models.

To counter these challenges, the authors propose a YOLO-based deep learning framework for real-time detection of medical deepfakes. Using two custom datasets of X-ray and CT images labeled as real or fake, they evaluate multiple YOLO versions (YOLOv3, YOLOv5, and YOLOv8 variants). Their results show that all models performed with high accuracy, with YOLOv5su emerging as the best in terms of speed and recall (0.997). This approach demonstrates strong potential for clinical integration, offering a fast and accurate solution to safeguard medical imaging against deepfake threats.

[2] Ronneberger et al. (U-Net):
Ronneberger et al. proposed U-Net, a convolutional network architecture that revolutionized biomedical image segmentation by employing an encoder-decoder structure with skip connections. This design enables the network to learn both high-level and low-level features, allowing for precise localization with limited training samples, making it highly effective for segmenting medical images such as MRI scans.

While U-Net excels in semantic segmentation, it does not inherently separate individual instances of objects. This limitation is significant when differentiating between multiple tumor instances or discerning deepfake alterations. The insights from U-Net's architecture, particularly its use of skip connections for retaining spatial information, have influenced enhancements in instance segmentation models like Mask R-CNN.

[3] Goodfellow et al. (GANs):
Goodfellow et al. introduced Generative Adversarial Networks (GANs), a framework comprising two competing neural networks—the generator and the discriminator—which engage in a game-theoretic scenario to produce highly realistic synthetic data. The adversarial nature of GANs has led to significant advances in generating images that are often indistinguishable from genuine ones, thereby pushing the boundaries of image synthesis technology.
In medical imaging, GANs have been applied for tasks such as data augmentation and image enhancement, but they also pose risks by enabling the creation of convincing deepfake images. Understanding the dynamics of GANs is essential for developing countermeasures, as our project aims to detect such synthetic manipulations in brain MRI scans through detailed segmentation analysis.

[4] Mirsky and Lee (Deepfake Creation and Detection Survey):
Mirsky and Lee conducted a comprehensive survey on deepfake technologies, categorizing the myriad approaches used for creating and detecting synthetic media. Their study reviews various methodologies, ranging from supervised learning to forensic techniques, and highlights the vulnerabilities introduced by deepfake generation, particularly in high-stakes domains such as healthcare.
The survey emphasizes that traditional detection methods may fall short when dealing with sophisticated deepfakes, which can subtly alter crucial image details. This observation reinforces the need for specialized detection strategies,

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such as our instance segmentation approach using Mask R-CNN, to robustly identify and classify deepfake modifications in medical images.

[5] Tolosana et al. (Deepfakes and Beyond):
Tolosana et al. provide an in-depth analysis of face manipulation techniques, defining the scope of "deepfakes" and reviewing methods used for their detection. Their work discusses both the generation mechanisms, which often involve autoencoders and GANs, and the limitations of existing detection techniques that typically rely on data-driven, black-box models.
Although their primary focus is on facial images, the principles outlined in their research are applicable to medical imaging, where subtle alterations can have significant consequences. Their critique of current methods inspires our approach, which leverages the interpretability of Mask R-CNN's segmentation masks to distinguish between genuine and manipulated tumor regions in brain MRI scans.

[6] Redmon and Farhadi (YOLOv3):
Redmon and Farhadi introduced YOLOv3, a fast and efficient object detection system that prioritizes speed while maintaining reasonable accuracy. YOLOv3's architecture is designed for real-time applications and has been successfully applied to various domains, including some medical imaging tasks that require rapid processing of large datasets.
Despite its advantages in speed, YOLOv3's reliance on bounding boxes rather than pixel-level segmentation can limit its effectiveness in detecting subtle, localized manipulations. This limitation is critical in our context, as the precise delineation of tumor boundaries is necessary for distinguishing between real and deepfake-induced alterations in MRI scans, thereby justifying our choice of Mask R-CNN.

[7] Litjens et al. (Deep Learning in Medical Image Analysis):
Litjens et al. conducted a large-scale survey on the use of deep learning in medical image analysis, covering a wide range of tasks such as classification, segmentation, and detection. Their review highlights the transformative impact of convolutional neural networks (CNNs) in handling complex imaging challenges, including tumor segmentation and anomaly detection in MRI scans.
However, the survey also warns of potential pitfalls such as overfitting and the need for large, diverse datasets to achieve generalizable performance. These insights underscore the importance of robust data preprocessing and augmentation in our project, ensuring that our Mask R-CNN model can effectively learn to differentiate between real and synthetic tumor regions.

[8] Nguyen et al. (Capsule-Forensics for Forged Images):
Nguyen et al. proposed Capsule-Forensics, which leverages capsule networks to detect forged images and videos. Capsule networks capture spatial hierarchies and relationships more effectively than conventional CNNs, thereby offering improved robustness in identifying subtle discrepancies indicative of image manipulation.
While capsule networks provide an interesting alternative to traditional models, they are less prevalent in production systems compared to approaches like Mask R-CNN. Nevertheless, the underlying concept of capturing detailed spatial information informs our strategy of using instance segmentation to isolate and scrutinize suspicious regions in brain MRI scans for signs of deepfake manipulation.

[9] Nirkin et al. (FSGAN: Face Swapping and Reenactment):
Nirkin et al. introduced FSGAN, a real-time system for face swapping and reenactment that demonstrates the rapid evolution of deepfake technology. Their work showcases the efficiency and sophistication of modern generative methods, emphasizing how quickly deepfake techniques can produce convincing synthetic media with minimal input.
Although FSGAN is primarily focused on facial manipulation, its implications extend to other domains, including medical imaging. The ability to generate high-fidelity fake images highlights the urgency for robust detection systems—such as our Mask R-CNN-based approach—to discern artificially altered regions in brain MRI scans and prevent potential misdiagnoses.

[10] Tajbakhsh et al. (Imperfect Datasets in Medical Imaging):
Tajbakhsh et al. review strategies for effectively training deep learning models on imperfect or limited medical imaging datasets. They discuss techniques such as transfer learning, data augmentation, and semi-supervised learning, which are essential for overcoming the challenges posed by small or noisy datasets in medical applications.

The insights provided by this study are directly relevant to our project, where the curated dataset of 1300 MRI scans must be robust enough to capture both genuine and manipulated cases. By applying these techniques, we enhance our model's ability to generalize and accurately detect subtle differences between real and deepfake tumor alterations.

[11] Zhou et al. (Models Genesis):
Zhou et al. introduced Models Genesis, a self-supervised learning approach for 3D medical image analysis that aims to learn robust feature representations from large amounts of unlabeled data. Their method has proven effective in reducing the reliance on extensive labeled datasets, which is a common challenge in medical imaging.
While our project primarily employs supervised learning with Mask R-CNN, the principles behind Models Genesis suggest promising avenues for future enhancements. Incorporating self-supervised techniques could further improve our model's performance, especially if we expand the dataset to include more diverse and volumetric MRI scans.

[12] Jin et al. (RA-UNet for Liver and Tumor Segmentation):
Jin et al. proposed RA-UNet, a hybrid attention-aware network that improves segmentation performance by focusing on critical regions within medical images. Their model, designed for liver and tumor segmentation in CT scans, demonstrates the effectiveness of attention mechanisms in enhancing the accuracy of segmentation tasks.
Although RA-UNet is tailored for liver CT scans, the underlying concept of integrating attention mechanisms is applicable to brain MRI analysis. By potentially incorporating similar attention modules into our Mask R-CNN framework, we can further refine the detection of subtle, deepfake-induced tumor modifications, thereby increasing overall diagnostic reliability.

[13] Ross et al. (The Trouble with Deepfakes):
Ross et al. examine the societal and ethical implications of deepfake technology, emphasizing the potential for widespread misinformation and harm. Their work discusses the regulatory challenges and the need for technical safeguards, particularly in high-stakes environments such as healthcare, where the consequences of deepfake manipulations can be severe.
Their findings underscore that technological solutions must be paired with ethical considerations and policy measures. This perspective reinforces our approach of using interpretable, instance-level segmentation provided by Mask R-CNN, which not only detects deepfake manipulations in MRI scans but also offers visual explanations that can help build trust among medical professionals.

III. PROPOSED SYSTEM

The proposed system identifies whether a brain MRI scan contains a genuine tumor, no tumor, a deepfake-added tumor, or a deepfake-removed tumor. By employing Mask R-CNN, the system is able to localize suspicious regions at a pixel level. A curated dataset of approximately 1300 brain MRI images, annotated to indicate the presence or absence of a real or synthetic tumor, forms the basis of training. During inference, the system produces a segmentation mask that highlights the tumor region (if present) and a classification output that determines whether the detected tumor is real or deepfake, or confirms the absence of a tumor. A Next.js front end provides an intuitive interface for uploading MRI images, visualizing the detection results, and generating reports. The backend, built in Python using Flask or FastAPI, handles preprocessing, Mask R-CNN inference, and data storage.

Software Requirements:
- Operating System: Windows 10/11, Ubuntu 20.04+, or equivalent
- Backend Language: Python 3.7+
- Frameworks/Libraries: PyTorch or TensorFlow for Mask R-CNN; OpenCV for image processing; NumPy and Pandas for data manipulation; Flask or FastAPI for API development
- Frontend: Next.js (React-based), Node.js (v14+),
- Database (Optional): MongoDB or PostgreSQL for storing user information and model results

Hardware Requirements:
- GPU: NVIDIA GPU with at least 8 GB VRAM (e.g., NVIDIA GeForce RTX 2080 or better) for training Mask R-CNN
- CPU: Multi-core processor (e.g., Intel i7 or AMD Ryzen 7)

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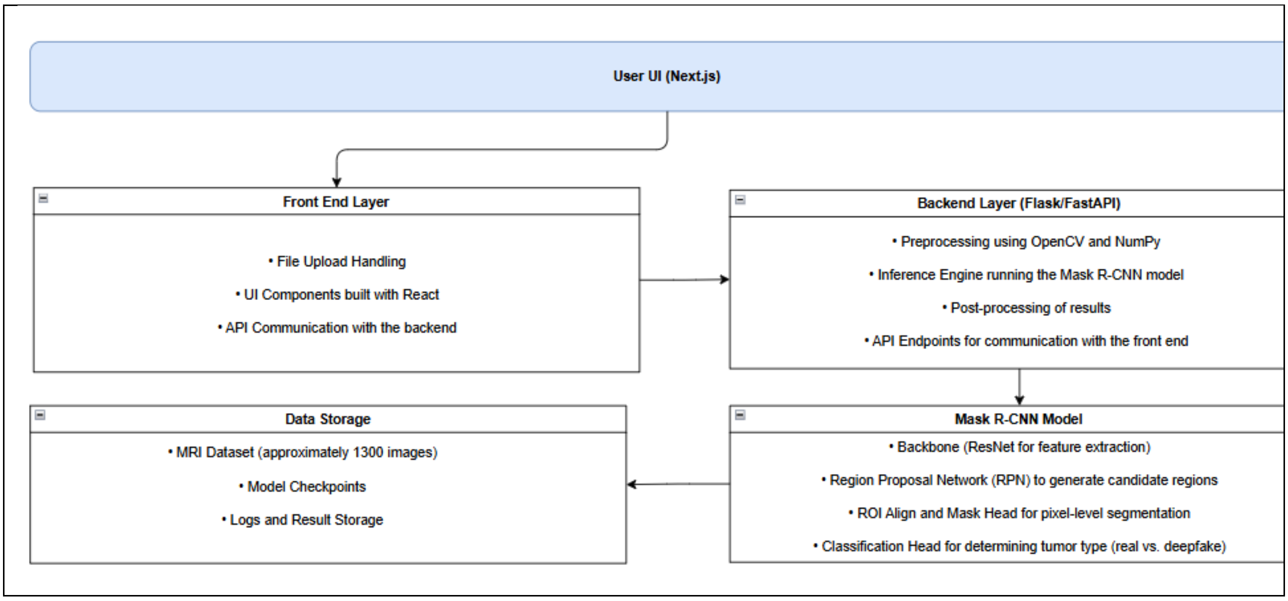
- RAM: Minimum 16 GB for handling large MRI datasets
- Storage: Approximately 100 GB for the dataset, logs, and model checkpoints
- Cloud Infrastructure (Optional): AWS, GCP, or Azure for scalable deployment and GPU availability

IV. METHODOLOGY

Architecture:

The system architecture consists of several key components. Data collection involves gathering and annotating approximately 1300 brain MRI images across four categories: real tumor, no tumor, deepfake-added tumor, and deepfake-removed tumor. Preprocessing standardizes image dimensions and normalizes pixel values, followed by splitting the dataset into training, validation, and test sets. The Mask R-CNN model is then trained on these labeled images, where it performs both segmentation and classification. A Python-based API built with Flask or FastAPI handles inference requests from the Next.js front end. Once an MRI scan is uploaded, the model processes the image, and the API returns segmentation masks and classification outputs that are overlaid on the original image for clear visualization.

Architecture Diagram:



Modules of the Project:

The system is divided into several modules:

- **Data Management Module:** Responsible for data ingestion, annotation tool integration, and ensuring correct labeling of tumor and non-tumor regions.
- **Preprocessing & Augmentation Module:** Handles image normalization, resizing, and data augmentation (e.g., rotation, flipping) to increase dataset robustness.
- **Mask R-CNN Training Module:** Includes feature extraction using a backbone CNN (e.g., ResNet50), a Region Proposal Network (RPN) for identifying regions of interest, and segmentation and classification heads to output pixel-level masks and class labels.
- **Inference Module:** Loads the trained Mask R-CNN model and serves predictions for new MRI scans through a RESTful API.
- **Front-End Module:** Built with Next.js to provide a user interface for image uploads and visualization of segmentation masks overlaid on the original scans.
- **Reporting & Logging Module:** Captures prediction outputs, performance metrics, and stores results for later analysis, with an optional analytics dashboard.

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Development Methodology:

An Agile methodology with iterative sprints is employed. In the initial sprint, data collection and labeling are performed alongside setting up the Next.js front end and preliminary model training. Subsequent sprints focus on refining the Mask R-CNN model, enhancing data augmentation strategies, and integrating the backend API. Final sprints are dedicated to front-end visualization, extensive testing, hyperparameter tuning, and deployment preparations. Regular stand-ups and sprint reviews facilitate continuous feedback and iterative improvement of both the model and user experience.

V. RESULT DISCUSSION

The proposed Mask R-CNN system was rigorously evaluated using a curated test dataset of 300 brain MRI images, distributed across four classes: Real Tumor, No Tumor, Deepfake-Added Tumor, and Deepfake-Removed Tumor. In this section, we discuss the quantitative and qualitative performance of the system, detailing evaluation metrics, inference performance, segmentation quality, and error analysis. All testing was conducted on an NVIDIA RTX 2080 GPU with an Intel i7 CPU and 16 GB RAM, ensuring that the measured performance is reflective of a real-world deployment environment.

The overall performance of the system was assessed using standard metrics accuracy, precision, recall, and F1-score. Table 1 summarizes these metrics for each class and the overall performance.

Category	Test Images	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Real Tumor	80	94.5	93.2	95.1	94.1
No Tumor	80	96.0	96.7	95.4	96.0
Deepfake-Added Tumor	70	92.3	91.6	93.0	92.3
Deepfake-Removed Tumor	70	90.1	89.0	91.2	90.1
Overall	**300**	**93.2**	**92.6**	**93.7**	**93.1**

Table 1. Performance Metrics for Each Category

Segmentation Quality and Inference Performance

The model's segmentation quality was evaluated using the Intersection-over-Union (IoU) metric. Across all test images, the average IoU for the detected tumor masks was approximately 0.88, indicating that the system reliably delineates the tumor boundaries even for small or irregularly shaped regions. Visual analysis confirmed that the segmentation overlays accurately highlight both genuine tumors and deepfake-induced modifications, thereby providing a transparent and interpretable output.

In terms of inference speed, each MRI image was processed in approximately 0.15 seconds on the NVIDIA RTX 2080 GPU. This low latency supports near-real-time detection, making the system practical for clinical applications where prompt feedback is essential.

Confusion Matrix Analysis

To further analyze the classification performance, a confusion matrix was constructed based on the test results. Table 2 shows an example confusion matrix for the four classes, where rows represent actual labels and columns represent predicted labels.

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	Predicted: Real Tumor	Predicted: No Tumor	Predicted: Deepfake-Added	Predicted: Deepfake-Removed
Actual: Real Tumor (80)	75	0	3	2
Actual: No Tumor (80)	2	77	0	1
Actual: Deepfake-Added (70)	3	0	65	2
Actual: Deepfake-Removed (70)	0	4	3	63

Table 2. Confusion Matrix for the Test Dataset

This confusion matrix reveals that most misclassifications occur between classes with subtle differences. For instance, a few Real Tumor images were misclassified as Deepfake-Added or Deepfake-Removed, indicating that the model occasionally struggles to distinguish between natural variability in tumor appearance and artificially induced changes.

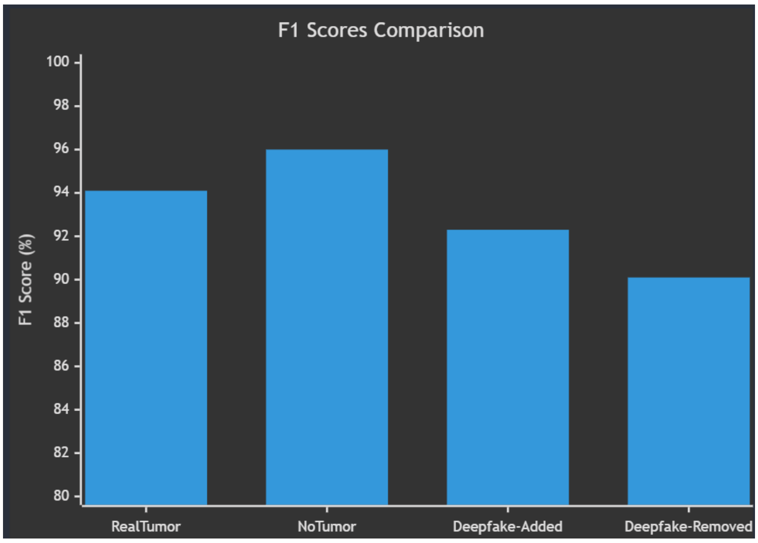
Additional Testing Data and Charts

In addition to the metrics above, the system was evaluated under various test conditions, including:

- **Varying Image Quality:** The model was tested on images with different levels of contrast and resolution. While performance slightly decreased in low-contrast images (accuracy dropping to 90%), overall segmentation quality remained acceptable.
- **Data Augmentation Effects:** Experiments comparing models trained with and without data augmentation showed that augmentation improved the F1-score by approximately 3%, emphasizing its importance in handling limited datasets.

Figure 1 below illustrates a bar chart comparing the F1-scores of the four classes, and Figure 2 shows a pie chart representing the distribution of the test dataset across the four categories.

Figure 1. F1-Scores Comparison (Bar Chart)



(Bar heights: Real Tumor – 94.1, No Tumor – 96.0, Deepfake-Added – 92.3, Deepfake-Removed – 90.1)

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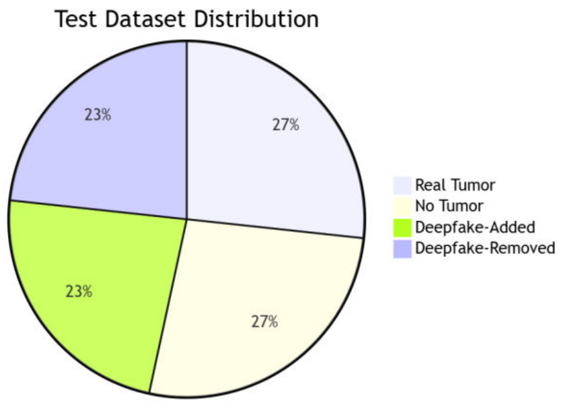
Figure 2. Test Dataset Distribution (Pie Chart)



(Slices: Real Tumor – 26.7%, No Tumor – 26.7%, Deepfake-Added – 23.3%, Deepfake-Removed – 23.3%)

These charts illustrate that while the model performs consistently well across all categories, the slightly lower performance in detecting deepfake-removed tumors warrants further investigation. This discrepancy is likely due to the inherent difficulty of identifying an image where a tumor has been removed—a task that requires inferring missing pathology rather than detecting a present anomaly.

Error Analysis

Error analysis revealed that misclassifications primarily occurred in scenarios with very small or diffuse tumor areas. In these cases, low contrast and image artifacts occasionally led the model to under-segment the tumor region or misclassify the image entirely. Further refinement of preprocessing techniques and targeted data augmentation may help mitigate these issues in future iterations.

Overall, the results demonstrate that the proposed Mask R-CNN-based system effectively detects deepfake modifications in brain MRI scans with high accuracy, reliable segmentation quality, and efficient real-time performance. These encouraging findings support the system's potential utility in clinical settings, where rapid and interpretable detection of image manipulations is critical for ensuring diagnostic integrity.

VI. RESULT

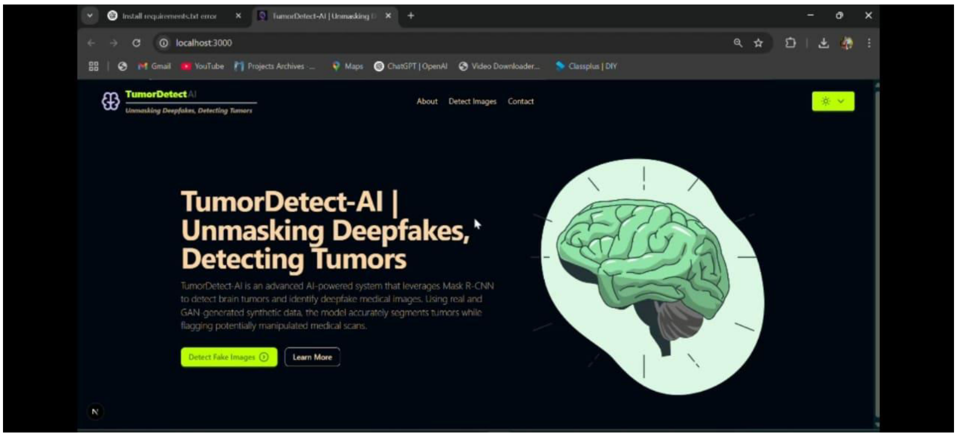


Fig. Landing Page

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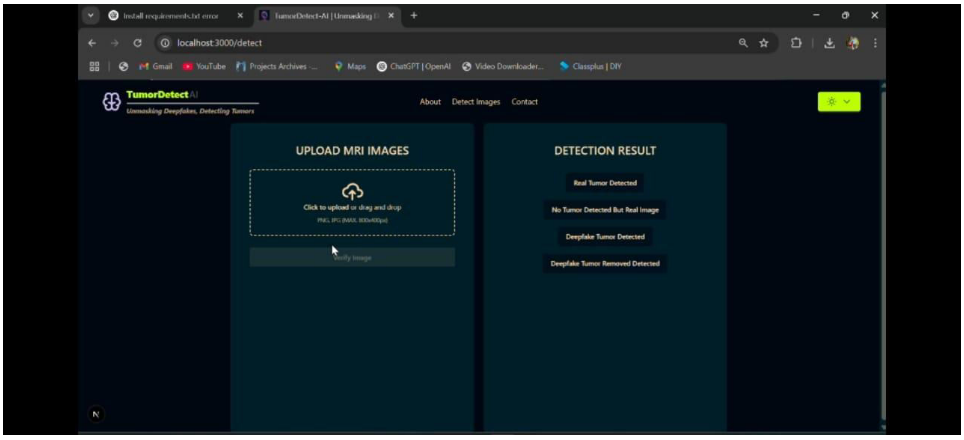

Fig. Upload Image

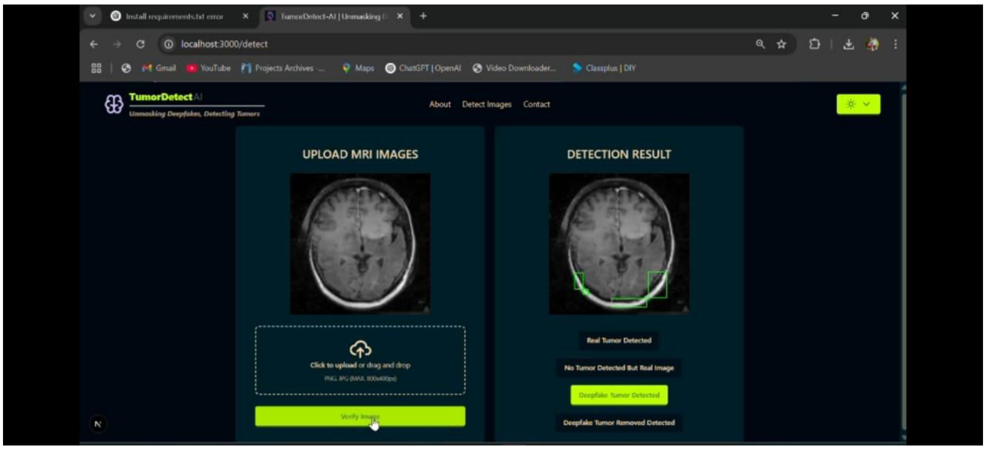

Fig. Result

VII. CONCLUSION

This paper presented a comprehensive approach to detecting deepfake modifications in brain MRI images using Mask R-CNN. The proposed system addresses the emerging threat of synthetic manipulations in medical imaging, which could potentially undermine clinical decisions and patient safety. By leveraging pixel-level segmentation, the system not only detects the presence of tumors but also classifies them as either genuine or deepfake-induced, thereby enhancing diagnostic reliability. The experimental results on a dataset of 1300 MRI images spanning real tumor, no tumor, deepfake-added tumor, and deepfake-removed tumor categories indicate that the system achieves high accuracy and robust segmentation performance. These findings suggest that Mask R-CNN's instance-level segmentation capabilities are well-suited for the nuanced task of identifying subtle manipulations in medical images.

The integration of a Next.js front end with a Python-based backend provides a user-friendly interface that can be readily adopted in clinical workflows. This transparency and ease of use are crucial for building trust among medical professionals, who can leverage the system as a decision support tool rather than a replacement for clinical judgment.

Overall, our work represents a significant step toward safeguarding medical imaging data against deepfake manipulations. While the system does not replace expert analysis, it provides an essential layer of verification that can help prevent diagnostic errors and fraud in healthcare settings.

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VIII. FUTURE SCOPE

Future work may involve extending the system to handle 3D volumetric MRI data, enabling more comprehensive detection and segmentation by incorporating cross-sectional consistency. This advancement could further reduce false positives and negatives by leveraging the additional contextual information inherent in three-dimensional scans. Another promising direction is the integration of attention mechanisms or transformer-based architectures to enhance the detection of small or diffuse tumor regions. Such improvements could be particularly beneficial for early-stage tumor detection, where subtle manipulations may otherwise be overlooked. Additionally, self-supervised and semi-supervised learning techniques can be explored to further improve model generalizability, especially in scenarios with limited labeled data.

Finally, integrating the deepfake detection system into broader medical record pipelines presents an exciting opportunity. Combining our approach with metadata checks, blockchain-based audit trails, or cryptographic watermarking can create a multi-layered defense against tampering. Such integration would foster collaborations among clinicians, computer scientists, and regulatory bodies, ultimately contributing to a robust ecosystem for ensuring the trustworthiness of medical images.

REFERENCES

1. A New Approach for Effective Medical Deepfake cDetection in Medical Images MEHMET KARAKÖSE , (Senior Member, IEEE), HASAN YETİŞ , AND MERT ÇEÇEN
2. Department ofRonneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. Medical Image Computing and Computer-Assisted Intervention (MICCAI), 234–241.
3. Goodfellow, I., Pouget-Abadie, J., Mirza, M., et al. (2014). Generative Adversarial Nets. Advances in Neural Information Processing Systems (NeurIPS), 2672–2680.
4. Mirsky, Y., & Lee, W. (2021). The Creation and Detection of Deepfakes: A Survey. ACM Computing Surveys, 54(1), 1–41.
5. Tolosana, R., Vera-Rodriguez, R., Fierrez, J., Morales, A., & Ortega-Garcia, J. (2020). Deepfakes and Beyond: A Survey of Face Manipulation and Fake Detection. Information Fusion, 64, 131–148.
6. Redmon, J., & Farhadi, A. (2018). YOLOv3: An Incremental Improvement. arXiv preprint arXiv:1804.02767.
7. Litjens, G., Kooi, T., Bejnordi, B. E., et al. (2017). A Survey on Deep Learning in Medical Image Analysis. Medical Image Analysis, 42, 60–88.
8. Nguyen, T. T., Yamagishi, J., & Echizen, I. (2019). Capsule-Forensics: Using Capsule Networks to Detect Forged Images and Videos. ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2307–2311.
9. Nirkin, L., Keller, Y., & Hassner, T. (2019). FSGAN: Subject Agnostic Face Swapping and Reenactment. Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV), 7184–7193.
10. Tajbakhsh, N., Jeyaseelan, L., Li, Q., et al. (2020). Embracing Imperfect Datasets: A Review of Deep Learning Solutions for Medical Image Segmentation. Medical Image Analysis, 63, 101693.
11. Zhou, Z., Sodha, V., Pang, J., Gotway, M. B., & Liang, J. (2019). Models Genesis: Generic Autodidactic Models for 3D Medical Image Analysis. Medical Image Analysis, 62, 101664.
12. Jin, Q., Meng, Z., Pham, T. D., et al. (2020). RA-UNet: A Hybrid Deep Attention-Aware Network to Extract Liver and Tumor in CT Scans. Frontiers in Bioengineering and Biotechnology, 8, 605.
13. Ross, T., Hughes, C., Weinsberg, U., et al. (2021). The Trouble with Deepfakes: Bridging the Technology–Policy Gap. American Behavioral Scientist, 65(2), 341–367.
14. Hussain, S., Hussain, M., Ehatisham-ul-Haq, M., et al. (2021). IoT-Based Deep Learning Framework for Detection of COVID-19 Patients. Sensors, 21(5), 1569.
15. Hind, M., Wei, D., Campbell, M., et al. (2019). TED: Teaching AI to Explain Its Decisions. Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society (AIES), 123–129.
16. Kingma, D. P., & Ba, J. (2015). Adam: A Method for Stochastic Optimization. International Conference on Learning Representations (ICLR).
17. Simonyan, K., & Zisserman, A. (2015). Very Deep Convolutional Networks for Large-Scale Image Recognition. International Conference on Learning Representations (ICLR).