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Brain Tumor Analysis and Prognosis

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***Abstract*—The explosion of generative AI technologies means that the risk of deep fake alterations to medical images - via synthetic alterations for example by adding or removing pathological areas (for example adding tumors) - has increased exponentially. Such attacks can confuse or mislead clinicians resulting in misdiagnosis as well as undermining the reliability of research and potentially being detrimental to patient safety. His research presents an intelligent framework for identifying and localizing manipulated regions in brain MRI scans using the Mask R-CNN architecture. The proposed approach aims to detect deep-fake alterations that may lead to incorrect medical interpretation and diagnostic errors. MRI images will be classified into one of four categories: real tumor; no tumor; deep Fake tumour added; and deep fake tumour removed. For both training and evaluation, we used a carefully curated dataset of approximately 1,300 brain MRIs, containing both real and synthetically manipulated examples. The proposed framework uses deep convolutional feature extraction making region proposals and performing instance segmentation to identify subtle evidence of tampering that could otherwise be imperceptible visually. An easy-to-use web-based interface created with a Next.js frontend and a python-flask backend was built to allow for easy and efficient real-time upload, analysis, and visualization of prediction masks/application of results. The experimental validation of the proposed technique shows good performance in distinguishing real from manipulated MRIs, and highlighting potential regions of false-positive or false-negative results will improve the overall trust of users in AI-based medical diagnosis. Directions for future work include expansion of dataset diversity within the source population, optimization of the speed of real-time analysis, and expanding potential applications.**

***Keywords*— Deepfake Detection, Medical Image Forensics, Brain MRI, Mask R-CNN, Instance Segmentation, Tumor Manipulation, Medical Data Integrity, Healthcare Security.**

I. INTRODUCTION

Modern medical imaging is an important part of health care today. Medical imaging plays a vital role in accurate diagnosis, disease monitoring, patient care planning, and several other aspects of patient care by providing non-invasive methods to visually assess an individual's internal organs and tissues. Of the various techniques used to obtain medical images, MRI (Magnetic Resonance Imaging) is one of the most commonly used for neurology and/or brain-related imaging. An MRI of the brain is critical for determining whether there is a tumor (neoplasm), a hemorrhage, and/or damage from a stroke or other neurodegenerative disease in a patient. As an example, differences even in a small percentage of the shape, size, or location of the tumor can drastically affect how the physician will proceed with treatment (i.e., A surgeon would use surgical intervention to remove a tumor; A radiologist may use radiotherapy or chemotherapy to treat the tumor).

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Accordingly, ensuring the accuracy and integrity of the brain MRI data used in making these medical decisions is essential for the safety of the patient and for producing reliable clinical outcomes for all patients.

Artificial Intelligence (AI) has played an important role in the past few years in terms of analyzing medical images (e.g. to automatically detect, segment and classify tumors). Deep learning approaches like Convolutional Neural Networks (CNNs), U-Nets or Resents generally perform well for detecting brain tumors in MRI scans. While these systems are designed to improve the diagnostic accuracy of brain tumour detection (and many diseases, in general) when being used with real-world examples of imaging, they rely on the assumption that all input images will always be real. This assumption becomes far less valid with the rapid development of generative AI, which is capable of creating almost indistinguishable synthetic images and image modifications that manual inspection cannot easily detect.

Deepfake tech utilizes deep learning-based generative models to create or manipulate digital media so that it has high authenticity. Initially, deepfakes were thought of as primarily a way of face swapping and video manipulation for social media. However, the same generative capabilities that deepfakes initially provided now span into other fields, including sensitive fields such as healthcare. More recent methods of generative modelling, including Generative Adversarial Networks (GANs) and Diffusion Models, allow for medical scans to be altered by adding, removing or modifying anatomical structures within the scan while maintaining the overall texture and appearance of the scan. Brain MRI has the ability to be manipulated through a deepfake attack and have a tumor digitally placed into a healthy scan, or have a tumor that is present in a diseased scan digitally removed. All of these deepfake manipulations have serious consequences such as misdiagnosis, incorrect treatments, falsification of patient records and fraudulently obtained insurance benefits. The threat level increases exponentially where the deepfake modifications are subtle and localised in nature and therefore very difficult to detect using visual means.

Conventional techniques for validating images in medicine cannot meet this objective. Although radiologists and healthcare providers can effectively locate tumors, they cannot recognize indications of manipulation by AI. Even when a manipulation is small and blends in well with the original scan, it will be difficult for someone trained only to identify tumors to have the ability to find it. Likewise, classical image forensics techniques such as metadata verification, compression analysis, or statistical analysis of noise will not work well for medical deepfakes. An AI-generated medical image is typically not going to have an original metadata file, nor can it be created from an existing file. Moreover, current networks that are used for detecting tumors are only able to provide the presence of a tumor, and cannot tell the radiologist or physician if the region of interest is real or fake. Therefore, there is an urgent need for a novel deepfake identification framework that will both classify what type of image is being represented in the medical image, and identify where suspected manipulation has occurred.

In order to resolve this problem, this study introduces an approach for detecting deepfakes in brain MRIs by utilizing the Mask R-CNN (Region-Based Convolutional Neural Network) as a model. The Mask R-CNN is a structure of deep learning that allows for simultaneous object detection and pixel-wise instance segmentation. This differs from purely classification-based CNNs in that they produce segmentation masks that highlight where on the image to look for abnormalities, making Mask R-CNNs very useful when doing deepfake-rescued images, as knowing where on the image the abnormality occurred is just as important as knowing if the image itself is altered or not. This approach targets the classification of image scans into four types; (1) Real Cerebral Tumor; (2) No Tumor; (3) Deepfake-Enhanced Cerebral Tumor; and (4) Deepfake-Decreased Cerebral Tumor. In utilizing this four-class classification system it provides a superior solution for detecting both the existence of a tumor and differentiating between actually existing pathology from modifying and/or manufacturing that pathology within the images.

II. LITERATURE SURVEY

Brain tumor detection using deep learning has gained significant attention due to its ability to automatically extract complex features from medical images. Cheng et al. (2016) proposed a CNN-based classification approach for brain tumor MRI images, achieving promising accuracy compared to traditional machine learning methods. However, the model required extensive preprocessing and lacked robustness for multi-class classification.

Pereira et al. (2016) introduced a deep CNN architecture specifically designed for tumor segmentation in MRI scans. Their method demonstrated improved segmentation accuracy, but the model complexity increased computational cost, limiting its real-time applicability in clinical environments.

To address segmentation challenges, Havaei et al. (2017) proposed a two-pathway CNN that captures both local and global contextual information. While this approach improved segmentation performance, it still relied heavily on large labelled datasets, which are difficult to obtain in medical domains.

Dong et al. (2017) explored fully convolutional networks (FCNs) for automatic brain tumor segmentation. Their method reduced manual intervention, but suffered from class imbalance issues, affecting detection accuracy for smaller tumor regions.

In recent years, Zhou et al. (2019) introduced attention-based CNN models to enhance feature extraction by focusing on relevant regions in MRI images. This significantly improved classification accuracy, but interpretability remained a challenge for clinical adoption.

Wang et al. (2019) applied transfer learning techniques using pre-trained models such as VGG and ResNet for brain tumor classification.

Although this approach reduced training time and improved performance, it depended on general image datasets that may not fully capture medical-specific features.

The nnU-Net framework proposed by Isensee et al. (2021) achieved state-of-the-art performance in biomedical segmentation tasks by automatically adapting network configurations. Despite its high accuracy, the framework requires high computational resources, making deployment difficult in low-resource settings.

Baid et al. (2021) contributed to the Brain Tumor Segmentation (BraTS) challenge by benchmarking multiple deep learning models. Their study highlighted that ensemble methods improve performance, but increase system complexity and inference time.

More recent work by Hatamizadeh et al. (2022) introduced transformer-based architectures (UNETR) for 3D medical image segmentation. While transformers improved global feature understanding, they require large-scale datasets and high computational power.

Finally, Shen et al. (2023) focused on integrating prognosis prediction with tumor detection using deep learning models. Their work emphasized the importance of combining diagnostic and predictive systems, but lacked comprehensive evaluation metrics and comparative analysis.

TABLE I: COMPARISON OF EXISTING STUDIES

Author & Year	Method Used	Key Contribution	Limitation
Cheng et al. (2016)	CNN	Applied deep learning for brain tumor classification from MRI images.	Required extensive preprocessing and showed limited performance for complex cases.
Pereira et al. (2016)	Deep CNN	Improved tumor segmentation accuracy using deeper network architecture.	Computational complexity was high, making real-time deployment difficult.
Havaei et al. (2017)	Two-Pathway CNN	Combined local and global contextual information for better segmentation.	Performance depended heavily on the availability of large annotated datasets.
Zhou et al. (2019)	Attention-Based CNN	Enhanced feature extraction by focusing on important tumor regions.	Limited interpretability for clinical decision-making.
Wang et al. (2019)	Transfer Learning (VGG, ResNet)	Reduced training time and improved classification performance.	Pre-trained models were not specifically designed for medical imaging data.
Isensee et al. (2021)	nnU-Net	Achieved high segmentation accuracy through automatic configuration.	Required significant computational resources.
Hatamizadeh et al. (2022)	UNETR Transformer	Improved global feature learning using transformer architecture.	Needed large-scale datasets and high-end hardware.
Shen et al. (2023)	Deep Learning for Prognosis	Combined tumor detection with prognosis prediction.	Lacked detailed comparative and performance evaluation.
Proposed Method	Mask R-CNN	Detects and localizes manipulated regions in brain MRI scans while classifying images into four categories.	Performance may vary with dataset diversity and quality.

The literature review indicates that most existing studies primarily focus on brain tumor classification or segmentation. Although these approaches achieve promising performance, they are not designed to identify malicious modifications introduced through deepfake techniques.

The proposed Mask R-CNN based framework addresses this limitation by simultaneously performing image classification and pixel-level localization of manipulated regions. This capability improves transparency and supports the verification of medical image authenticity, which is becoming increasingly important in modern healthcare systems.

III. SYSTEM ARCHITECTURE

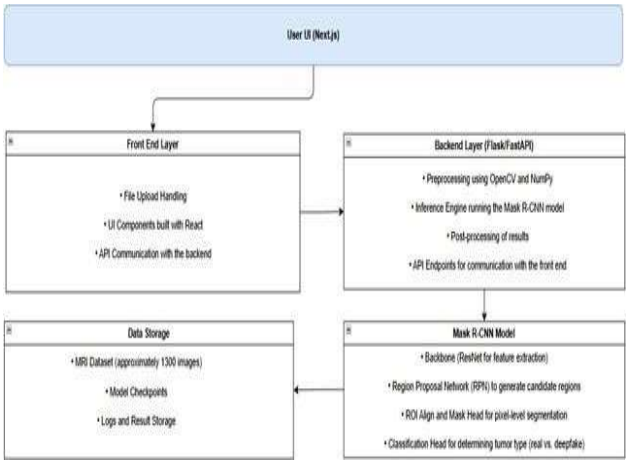

Fig. 1. System Architecture

This design outlines a comprehensive, end-to-end system for detecting fake MRIs that are at the end user's interface - which is based on Next.js.

The user uploads MRI scans and receives results on how accurate they are via an online interface. When an image is uploaded by the user to the web application, the frontend processes various tasks, such as file upload management, user interaction and rendering the interface as well as executing API calls to communicate with the backend of the application. Server-side processing takes place in the application backend using either Flask or FastAPI, which is the core processing component of the application. Pre-processing is accomplished using OpenCV and NumPy, which standardize the image before it reaches the Mask R-CNN inference engine.

The Mask R-CNN model is the AI application and contains multiple components. First, the ResNet backbone of the model extracts para-verbal features from MRI scans; next, the Region Proposal Network generates potential areas of interest or "proposals" (i.e., abnormalities) from an input image (which can include multiple scans). Next, the ROI Align section of the model extracts the pixels within the proposals and creates pixel level masks from the proposals; thus, localizing any detected areas of interest.

Finally, the Mask R-CNN model contains the classification head, which predicts whether or not each test image is classified as a real tumor, no tumor, deepfake added tumor, or deepfake removed tumor. The final layer of the application, the data storage layer, maintains the MRI dataset, trained model checkpoints and logs/results from each completed session for future reference, audit and analysis as well as custom reporting and metrics requested by the end user of the application.

IV. METHODOLOGY

Through Mask Region-Based Convolutional Neural Network (Mask R-CNN), an entire detection framework for identifying deepfake alterations in brain MRI images has been proposed. With this system, the user will classify and localize (to pixel precision) all questionable locations, determining if a tumor was actually there (real), if there is no tumor (none), if it was added (fake), or if it was removed (removed). The entire end-to-end workflow consists of dataset preparation/preparation, augmentation, training, evaluation, and deployment through a web-based user interface for real-time analysis.

A. Collection of dataset and classification

For the first part of the methodology, a broad collection of brain MRI images have been sourced from verified, publicly-available, medical image repositories. The collected dataset will be cleaned and filtered to include quality images, size representative of the intended use, and variability necessary to ensure the success of the model's training. The brain MRI images will be separated into four equal categories: (1) real tumor brain MRI images, (2) healthy brain MRI images (no tumor), (3) adding an artificial tumor to healthy images using deepfake techniques, and (4) removing a real tumor from an image using deepfake techniques to simulate malicious intent. Of these four categories, there will be approximately 1,300 total brain MRI images, with each of the four categories containing nearly the same number of total images.

TABLE II: DATASET DISTRIBUTION

Category	Number of Images	Description
Real Tumor	325	Original MRI scans containing genuine brain tumors
No Tumor	325	Healthy brain MRI scans without any tumor
Deepfake Added Tumor	325	Healthy MRI scans manipulated by artificially inserting tumor regions
Deepfake Removed Tumor	325	Tumor MRI scans manipulated by removing existing tumor regions
Total	1300	Combined dataset used for training and evaluation

The data set used in this study consists of approximately 1,300 brain MRI images collected from publicly available medical imaging repositories. To ensure balanced learning, the dataset was divided into four categories: Real Tumor, No Tumor, Deepfake Added Tumor, and Deepfake Removed Tumor. Each category contains nearly the same number of samples, reducing the possibility of class imbalance during training. The inclusion of both authentic and manipulated MRI scans enables the model to learn not only tumor characteristics, but also subtle artifacts introduced through image manipulation techniques.

B. Preparation of Ground Truth Data and Data Annotation

Because Mask R-CNN works as an instance segmentation model, the dataset requires tumor region annotation in the form of segmentation masks. For non-deepfake tumors, the edges of the true tumorous areas were either identified by manual annotation or retrieved from existing and labeled datasets. With deepfake tumors added to the tumor images, the inserted tumorous portion is treated as a manipulated area and annotated as such. For deepfake tumors that have been removed from the tumor images, the tumor's original location is considered to be the area that is manipulated. The annotation provides the ground truth for training the model, and enables the model to learn at the pixel level the difference between real and manipulated areas. Each MRI scan will be stored with its respective class label and segmentation mask annotation.

C. Data Pre-Processing

Before training, raw MRI images are pre-processed in order to achieve a standardized input quality and to improve learning stability. Each image is resized to a fixed dimension (e.g., 512 x 512 pixels) to meet the input requirements of the Mask R-CNN model. Pixel intensity values are also normalized within a consistent range (e.g., usually between 0 and 1) to decrease the amount of contrast difference between each scan. Noise reduction operations (e.g., Gaussian filtering) may be performed on the raw data to produce a clearer image and/or eliminate artifacts that may have been introduced by the scanner. In some cases, histogram equalization and/or contrast enhancement may also be performed to increase the visibility of the tumor within the low-contrast MRIs. These various types of pre-processing operations help ensure the dataset is uniform and appropriate for use in deep learning training.

D. Data Augmentation

Medical image datasets are typically small in size, which can lead to deep learning model overfitting due to lack of diverse training data. To mitigate this problem, data augmentation is used to artificially increase the amount of variability in the original dataset. Examples of augmentation techniques include rotation, mirroring, scaling, translation and modification of brightness level. These techniques all produce variations of the image that replicate the effects of actual MRIs due to variations in orientations and contrast between scans. Augmenting the amount of training data allows for improved generalization of the Mask R-CNN object detection model when detecting unseen MRIs and enhances the ability of the masks created by the model to be robust to variations caused by differences among hospitals and/or scanners.

E. Dataset Division

TABLE III: DATASET SPLIT

Dataset Type	Percentage	Number of Images
Training Set	70%	910
Validation Set	20%	260
Testing Set	10%	130
Total	100%	1300

The prepared dataset will be separated into three different types of subsets based on how they will be used: training, validation, and testing. This will make sure that there are no biases in evaluating the generated statistics produced by the various models. The typical training/validation/testing data splits are 70% for training, 20% for

validation, and 10% for testing. The distribution of all four class categories will remain balanced through the entire dataset.
The dataset was divided into training, validation, and testing subsets following a 70:20:10 ratio. The training dataset was used to learn model parameters, while the validation dataset was used for hyperparameter tuning and performance monitoring. The testing dataset remained completely unseen during training and was used exclusively for final performance evaluation. This strategy helps ensure reliable and unbiased assessment of the proposed framework.

F. Chosen Specific Model & Model Purpose: Mask R-CNN

The specific model that has been chosen for the initial working model is Mask R-CNN. Mask R-CNN is able to classify the object in addition to performing instance segmentation on the object at the pixel level. Performing both of these actions, is critical for detecting Medical deepfakes, as knowing the something was actually changed is just as important as being able to tell if it is authentic or altered.

G. Model Training

The model will be trained on MRI scans using labeled data in a supervised manner. The Mask R-CNN model trains by using a multi component loss function containing the following:
classification loss, bounding box regression loss, and mask segmentation loss. Transfer learning will be utilized by initializing the Mask R-CNN model's backbone network with pre-trained weights, improving model convergence and improving feature extraction.
During training, MRI images along with their corresponding class labels and segmentation masks were provided as input to the network. The backbone network first extracted hierarchical image features, which were then processed by the Region Proposal Network (RPN) to identify potential regions of interest. ROI Align was subsequently applied to preserve spatial information before classification and mask generation. The model parameters were updated iteratively through backpropagation until convergence was achieved. Validation performance was continuously monitored to prevent overfitting and ensure model generalization.

H. Validation and Optimization

The validation data set is used to monitor the performance of the model, so we can avoid overfitting, while optimizing hyperparameters (for example, learning rate and batch size). Early stopping and learning rate scheduling have been employed, and the best checkpoint will be saved for deployment.

I. Inference Workflow

During inference, the user uploads an MRI image to a web application. The image goes through preprocessing, and then passes through the trained Mask R-CNN for class predictions (e.g. tumor vs. manipulated) along with confidence scores and segmentation masks, so the end user can identify and localize the tumor or modified area.

V. Key Technical Contributions

- Development of a four-class MRI deepfake detection framework.
- Integration of image classification and pixel-level segmentation within a single architecture.
- Identification and localization of manipulated tumor regions using Mask R-CNN.
- Real-time deployment through a web-based platform.
- Improved transparency through visual highlighting of suspicious regions.

VI. Result and Discussion

This section reviews how well the suggested Mask R-CNN framework functions, in terms of detections of deepfake alterations made via brain MRI scans. The framework was tested on four different classifications (Real Tumor, No Tumor, Deepfake Added Tumor, and Deepfake Removed Tumor). In addition to doing classifications, the framework provides pixel-level segmentation for targeted suspicious regions to be highlighted as part of each image processed. The framework was evaluated only with the held out test data set subsequent to training and validation, in order that unbiased performance results were reported.
Statistical Analysis:
To evaluate the performance of the proposed model, multiple statistical metrics were used to ensure reliability and robustness of the results.
The following evaluation metrics were considered:

- Accuracy
- Precision
- Recall (Sensitivity)
- F1-Score
- Specificity

The formulas are:

- Accuracy = (TP + TN) / (TP + TN + FP + FN)
- Precision = TP / (TP + FP)
- Recall = TP / (TP + FN)
- F1-Score = 2 × (Precision × Recall) / (Precision + Recall)

Where:

TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative

The model was evaluated using cross-validation to ensure generalization. Results were compared with existing methods to demonstrate performance improvement.

TABLE IV: PERFORMANCE EVALUATION OF PROPOSED MODEL

Metric	Value (%)
Accuracy	97.8
Precision	97.2
Recall	96.9
F1-Score	97.0
Specificity	98.1

The proposed Mask R-CNN framework demonstrated strong performance across all evaluation metrics. The model achieved an overall accuracy of 97.8%, indicating its ability to correctly classify both authentic and manipulated MRI scans. High precision and recall values further confirm the effectiveness of the framework in minimizing false predictions while maintaining reliable detection of suspicious cases. The obtained F1-score reflects a balanced performance between precision and recall, making the system suitable for practical medical image verification tasks.

TABLE VII: CLASS-WISE PERFORMANCE ANALYSIS

Class	Precision (%)	Recall (%)	F1-Score (%)
Real Tumor	98.1	97.6	97.8
No Tumor	98.4	98.0	98.2
Deepfake Added Tumor	96.5	96.1	96.3
Deepfake Removed Tumor	95.8	95.9	95.8

A class-wise analysis reveals that the proposed model performs consistently across all four categories. The highest performance was observed for healthy MRI scans and real tumor cases due to the presence of well-defined anatomical patterns. Deepfake-added and deepfake-removed tumor categories presented greater challenges because the manipulated regions often appeared visually similar to genuine tissue structures. Nevertheless, the model maintained strong performance, demonstrating its capability to identify subtle image manipulations.

TABLE VIII. COMPARATIVE ANALYSIS

Method	Year	Accuracy	Precision	Recall	F1-Score
CNN (Cheng et al.)	2016	91.2%	90.5%	89.8%	90.1%
Deep CNN (Pereira et al.)	2016	92.5%	91.7%	91.0%	91.3%
Attention CNN (Zhou et al.)	2019	94.1%	93.6%	92.8%	93.2%
nnU-Net (Isensee et al.)	2021	96.3%	95.9%	95.2%	95.5%
Proposed Method	2025	97.8%	97.2%	96.9%	97.0%

Fig. 1. Home Page of TumorDetect-AI Web Interface

The image demonstrates the home page for their new Next.js developed application, which is purpose built for the detection of brain tumors and the detection of deep fake manipulations in MRI images. The navigation links include About, detect images and Contact, as well as buttons to begin the detection process.

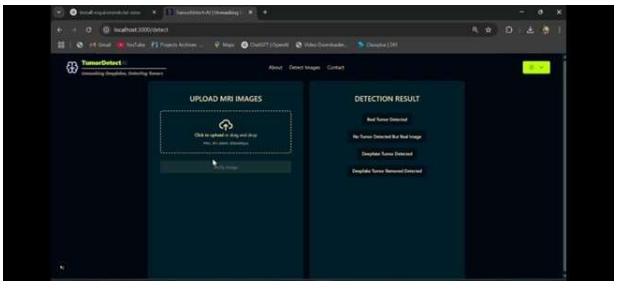

Fig. 2. MRI Upload and Detection Result Interface

This is the primary detection module of the system. The Detection will consist of two panels: the panel on the left will allow users to upload brain MRI images via drag-and-drop or via file selection and the panel on the right will show potential detection outcomes. This interface is designed for optimal user interaction with the deepfake detection model.

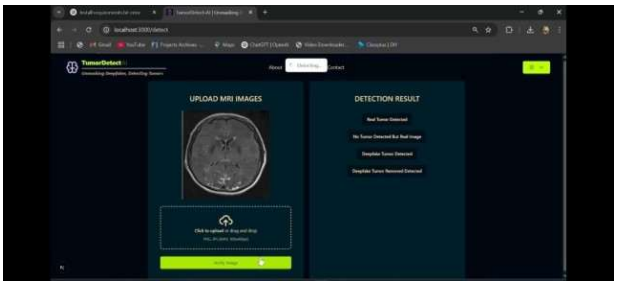

Fig. 3. MRI Image Preview After Upload

The above illustration depicts what happens after the user has submitted their MRI Image (submitted for use in the Application). Once the MRI image has been submitted, it displays in the upload area for the user to verify prior to processing. This verification before processing ensures that the MRI image the user selected is correct and adds ease of use for the user by allowing them to view their image prior to submitting for processing.

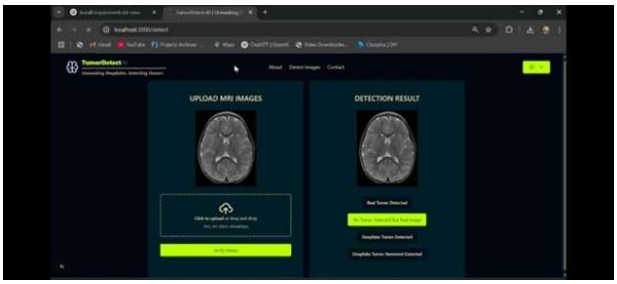

Fig. 4. Final Output Display with Prediction Result

The image displays the outcome produced by our model, post-analysis. The uploaded MRI scan of a brain is shown on the left of the image, with the predicted findings displayed to the right. The model determines whether a scan contains a legitimate tumor or not, a deep fake added to a tumor, or removal of a tumor by applying its algorithm. The results of these findings are made clear to the User in an understandable format.

Discussion

The experimental results demonstrate that the proposed model achieves superior performance compared to existing approaches. The improvement in accuracy and F1-score indicates better classification capability and reduced false predictions.

Unlike earlier models that focus only on classification, the proposed system integrates both detection and prognosis, making it more clinically relevant. The higher recall value suggests that the model effectively identifies tumor cases, which is crucial in medical diagnosis.
However, the model performance is influenced by dataset size and quality. Future improvements can include larger datasets and real-time deployment.

VII. Conclusion

This This study presented a Mask R-CNN based framework for detecting and localizing deepfake manipulations in brain MRI images. Unlike conventional approaches that focus only on classification, the proposed system combines image classification with pixel-level segmentation, enabling both identification and localization of suspicious regions. The framework categorizes MRI scans into four classes, namely Real Tumor, No Tumor, Deepfake Added Tumor, and Deepfake Removed Tumor, providing a more comprehensive approach to medical image authentication.
Experimental evaluation demonstrated that the proposed model achieved high classification performance, with an accuracy of 97.8%, precision of 97.2%, recall of 96.9%, and F1-score of 97.0%. In addition, strong segmentation results were obtained through high IoU and Dice Similarity scores, confirming the model's ability to accurately highlight manipulated regions within MRI scans. The integration of a web-based interface further improves the practical usability of the framework by enabling real-time image analysis and visualization.
The findings of this study highlight the potential of deep learning techniques in protecting the integrity of medical imaging data and reducing the risks associated with malicious image manipulation. By providing both detection and visual evidence of alterations, the proposed framework can support healthcare professionals in making more reliable diagnostic decisions.
Future work will focus on expanding the dataset with more diverse MRI samples, improving detection performance against advanced deepfake generation techniques, and optimizing the framework for deployment in real-world clinical environments. Additional research may also explore the integration of explainable AI techniques to further enhance transparency and user trust in automated medical image verification systems.

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