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Design And Development Of Flask-Based Web Application For Brain Tumor Detection Through MRI Images And Federated Learning

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***Abstract** -In response to the increasing prevalence of brain tumors, our research focuses on pioneering diagnostic methods through a revolutionary approach. Leveraging federated learning and machine learning, we aim to create an advanced brain tumor detection model that surpasses existing accuracy standards while championing a decentralized paradigm to ensure patient data privacy. The methodology involves meticulous acquisition and preprocessing of diverse MRI datasets, emphasizing standardization and extracting crucial features like tumor intensity and tissue regions. Our central detection model employs a Convolutional Neural Network (CNN) trained on this curated dataset, with a distinctive feature being the incorporation of federated learning for decentralized model training, eliminating the need for centralized data gathering to protect sensitive medical information.*

Our user-centric approach is reflected in a user-friendly Flask-based web application allowing easy MRI image uploads from homes. The CNN architecture is tailored for precise brain tumor detection, with continuous improvement driven by user feedback. Rigorous evaluations ensure reliable and accurate results, with an extension to group segmentation enhancing utility in healthcare settings. Emphasizing privacy and data security, our design aligns with healthcare regulations, implementing encryption measures during data transmission and storage.

The integration of federated learning into brain tumor identification from MRI images is a seamless aspect of our research. Employing an ensemble of CNN models selected based on performance, the federated learning model is developed using this architecture. Experimental results demonstrate the efficacy of federated learning, achieving a commendable accuracy of 91.05%, ensuring privacy-protected tumor classification without significant compromises in accuracy. This research signifies a significant advancement in brain tumor detection, combining federated learning and machine learning for elevated accuracy, while prioritizing patient privacy through a decentralized approach and a user-friendly web application, marking a transformative era in medical diagnostics. *Keywords: Federated learning, Image segmentation, Image classification, Computing methodologies, Privacy protection.*

I. INTRODUCTION

Increasing life expectancy poses a significant challenge in medical science, with technological advancements offering promising solutions. This paper focuses on brain tumor detection through MRI images and Federated Learning, aiming for accurate classification of different

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tumor types. Employing a decentralized approach to protect patient data confidentiality, the study utilizes federated learning with CNN algorithms, aiming to decrease computation time and enhance accuracy compared to traditional systems.

The research concentrates on gliomas, emphasizing precise tumor subregion segmentation for meaningful feature extraction. Leveraging the BraTS challenge dataset and deep ConvNets like VGG16 and ResNet50, the study aims to overcome detection delays, address patient privacy concerns, and reduce reliance on central servers. Additionally, the proposed web-based platform facilitates easy interpretation of detections for medical professionals and patients, contributing to advancing brain tumor detection methodologies with a focus on precision, efficiency, and accessibility in the medical context.

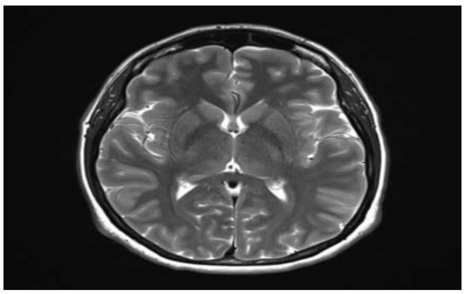

Fig.1 MRI scan of no tumor.

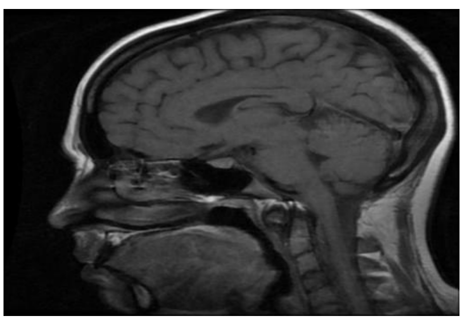

Fig2. MRI Scan with tumor

II.PAPER OVERVIEW

The review paper aims to develop a module for brain tumor detection utilizing Convolutional Neural Networks (CNN) while addressing concerns regarding centralized data collection through the implementation of Federated Learning (FL). The module endeavors to optimize execution time without compromising accuracy, ensuring minimal latency in the identification process.

The process commences with the acquisition of MRI scan images.Subsequently, data preprocessing techniques are employed to transform raw data into a comprehensible format, a crucial step in machine learning workflows.

The model's construction involves the utilization of CNN architecture. To ensure robustness and accuracy, the collected MRI Preprocessed scans sourced from various hospitals form a diverse and extensive dataset. The CNN algorithm then applies convolutional filters to scrutinize these images, discerning subtle variations and extracting intricate features pivotal for tumor detection.

Significance of the paper:

The research here aims to harness collaborative learning without centralizing sensitive medical information by employing federated learning techniques. The system proposed for brain tumor detection using CNN and FL techniques offers several benefits :

1. Employing the CNN algorithm and diverse MRI datasets enhances brain tumor detection accuracy and reliability.
2. Federated Learning ensures patient data privacy and confidentiality, addressing concerns about centralized data storage.
3. Collaboration and advancements in medical technology through machine learning enable timely access to accurate diagnostic information, expediting patient care and decision-making.

III. LITERATURE SURVEY

In their study, Author [1] utilized a 23-layer CNN on a dataset abundant in MRI images, achieving classification accuracies of up to 97.8% and 100%. The research presented two deep-learning models for detecting brain anomalies and classifying tumor grades, showcasing notable advancements in brain tumor diagnosis prediction.

In their study [2], researchers introduced a federated learning (FL) approach for brain tumor identification in MRI images, emphasizing data privacy. FL decentralizes data and coordinates model training on a central server, ensuring data ownership and privacy. Experimental results show a slight performance decrease compared to the base ensemble model, achieving 91.05% accuracy.

In [3], researchers introduced deep learning methods and machine learning approaches for early-stage diagnosis of brain tumors and healthy brains using MRI. The auto-encoder network and 2D CNN achieved notable training

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accuracies of 95.63% and 96.47%, respectively, after employing preprocessing and augmentation techniques.

In [4], the paper presents a brain tumor detection model employing machine learning algorithms, with CNN utilized for feature extraction and segmentation. The model achieves 97.79% accuracy on the training set but exhibits a significant disparity in loss, with 82.86% accuracy on the validation set.

In [5], researchers proposed machine learning algorithms to enhance brain tumor detection in MRI images, overcoming traditional classifier limitations. The study efficiently identifies cancer cells through MRI scans, achieving a training accuracy of 97.5% and a validation accuracy of 90.0%, with the best result reaching 91.09% accuracy, even without the pre-trained Keras model.

In [6], an innovative approach combines a 3D-UNet with an attention module to enhance brain tumor segmentation accuracy, surpassing existing techniques on the MSD dataset. The research contributes to advancements in medical image analysis while addressing concerns regarding data privacy and limited datasets in brain tumor segmentation.

In [7], the study introduces Federated Averaging (FedAvg) as a pioneering method for brain tumor classification, eliminating the need to share sensitive data. FedAvg delivers impressive results, achieving 98.69% accuracy on Independently and Identically Distributed (IID) data and over 93% accuracy on Non-Independently and Identically Distributed (Non-IID) data.

In [8], the research pioneers collaborative medical image segmentation through federated learning, emphasizing data privacy. Federated models achieve a Dice coefficient of 0.852 for multimodal brain scans, closely aligning with centralized models at 0.862, and outperforming other collaborative methods. This study underscores federated learning's effectiveness in maintaining data privacy while achieving segmentation performance comparable to centralized approaches.

In [9], the paper presents a three-stage brain tumor diagnostic system for MRI analysis, focusing on precise detection and segmentation. By improving image quality, employing advanced algorithms for tumor identification, and incorporating a post-processing stage, the system effectively overcomes challenges to robustly detect brain tumors in MRI images.

In [10], the paper underscores the urgency of swift and precise brain tumor detection, evaluating diverse methods with a focus on Edge Detection techniques. Emphasizing meticulous tumor localization for heightened accuracy, the study highlights the crucial role of image segmentation in efficiently isolating tumors from complex MRI images.

IV. PROBLEM STATEMENT

Improving life expectancy faces hurdles, with non-communicable diseases (NCDs) like heart disease, brain tumors, cancer, diabetes, and chronic lung diseases causing 60% of all deaths. Shared risk factors such as tobacco, alcohol, diet, and inactivity contribute to 80% of these deaths. Technological integration can aid in diagnosing and treating these diseases, thus enhancing survival rates and addressing health-related challenges.

Patient safety, a cornerstone of healthcare, faces threats to data security, prompting the need for solutions like federated learning to ensure patient data confidentiality. Technological advancements have revolutionized healthcare, driving the development of sophisticated medical devices, diagnostics, treatments, and healthcare systems. Concepts like machine learning (ML) and decentralized approaches offer promising solutions to improve disease prediction and management.

Early brain tumor detection is crucial, yet challenges persist. Decentralized disease detection systems, supported by local data centers, offer robust solutions, fostering data integrity and reducing corruption risks. These advancements enable earlier diagnoses, personalized treatments, and improved outcomes, ultimately reducing healthcare costs and mitigating symptom severity. With a high mortality rate in India and over 28,000 annual cases, urgent action is imperative to address this critical issue.

V. OBJECTIVE

This review paper aims to develop an accurate

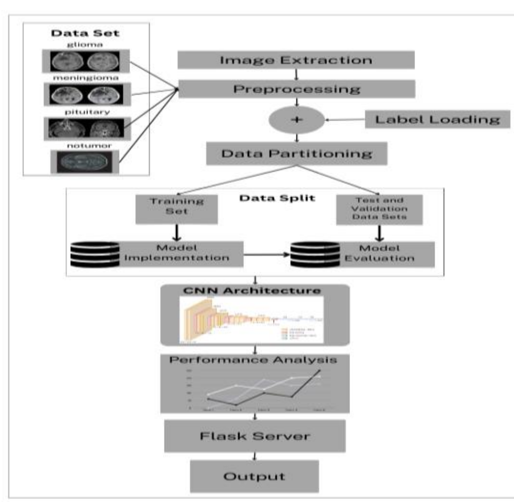

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Fig3. Flowchart of the model

efficient machine learning model for brain tumor detection using federated learning, prioritizing patient privacy and data security.

By leveraging federated learning techniques, the model can be trained on multiple devices without sharing raw data, ensuring data security through robust measures. Addressing challenges such as data combination, class imbalance, and model optimization, the study validates the accuracy and efficiency of the federated learning model on real-world data, comparing it with traditional approaches.

VI. PROPOSED APPROACH

The proposed system aims to streamline and enhance organizational efficiency by integrating advanced automation features, optimizing resource allocation, and fostering seamless communication across diverse functional units. The proposed system involves several key steps and components:

1. Centralized Data Gathering: The central problem is the challenge of centralized data gathering in the context of MRI-based brain tumor detection. Centralized MRI storage, a traditional approach, sparks privacy concerns in healthcare due to the paramount importance of patient confidentiality.

2. MRI Image Acquisition: The first step in brain tumor detection involves acquiring MRI scan images of patients. MRI images are a valuable diagnostic tool in healthcare, as they provide detailed information about the brain's structure and any potential abnormalities.

3. Federated Learning (FL): To address the issue of centralized data gathering and the associated data privacy concerns, the module leverages Federated Learning (FL). Federated Learning (FL) ensures privacy by enabling decentralized model training on local data, avoiding centralization of sensitive patient information, by sharing only model updates.

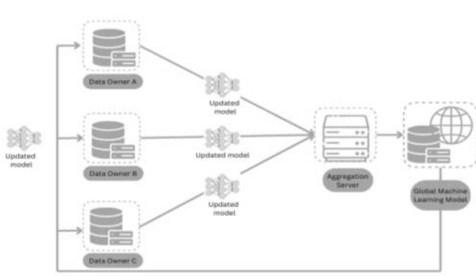

Fig4. Flowchart of Federated Learning

4. Data Pre-processing: After acquiring MRI scans, data preprocessing is applied. Data preprocessing is crucial for reading raw MRI data for machine learning models like Convolutional Neural Networks (CNNs). Data preprocessing involves tasks such as noise reduction, resizing, pixel value normalization, and other operations to ensure a consistent and suitable data format for analysis.

5. CNN Model Training and Testing: The pre-processed data is used to train a CNN model. CNNs are deep learning models well-suited for image analysis, including the detection of patterns and features in medical images. The model's accuracy and performance are evaluated using a distinct test dataset, assessing CNN's ability to detect brain tumors accurately in unseen data.

6. Group Segmentation of Medical Images: In addition to tumor detection, the module extends its capabilities to perform group segmentation of medical images. Image segmentation feature aids healthcare professionals in pinpointing the exact location and extent of tumor regions within MRI scans, offering valuable insights for diagnosis and treatment planning.

7. Resulting System for Brain Tumor Analysis: By integrating the aforementioned components, the module creates a comprehensive system for brain tumor analysis. This system integrates secure CNN-based brain tumor detection, FL for privacy, intuitive segmentation, and data integrity for comprehensive brain tumor analysis from MRI images.

VII. RESULT AND IMPLEMENTATION

In machine learning implementation, Jupyter Notebook offers versatility and interactivity. It starts with importing essential libraries like NumPy, Pandas, Scikit-learn, TensorFlow, and Keras, followed by preprocessing steps such as handling missing values, encoding categorical variables, and scaling features. The dataset is then split into training and testing sets for model training and evaluation. Training includes algorithm selection, hyperparameter tuning, and model fitting, with performance assessed using the testing dataset. Finally, fine-tuning hyperparameters optimizes model performance before deployment for predictions on new data.

VII.I Convolutional Neural Network

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A deep learning algorithm, CNN, a subset of machine learning, excels in analyzing visual imagery, making it ideal for classification and computer vision tasks. It particularly stands out in processing pictures, speech, or audio signal inputs. CNN consists of three main layers: the input layer, the convolutional layer, and the fully connected layer.

VII.II Federated Learning

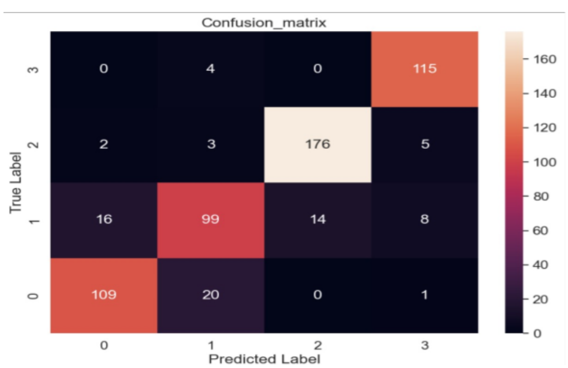
In brain tumor detection, Federated Learning is a unique approach prioritizing privacy and security by utilizing diverse datasets without centralizing sensitive patient data. This process involves establishing a federated learning system across multiple hospitals, independent model training, and collaborative model evaluation, ensuring effectiveness across diverse datasets.

VII.III Logistic Regression

As a supervised learning approach, Logistic Regression is a frequently used algorithm for predicting categorical dependent variables based on independent variables. It predicts the probability of a categorical outcome, providing values between 0 and 1. This algorithm is valuable for scenarios where the outcome is binary or categorical.

VII.IV Confusion Matrix

The confusion matrix serves as a pivotal tool for assessing classification model performance. It breaks down predictions into True Positives, True Negatives, False Positives, and False



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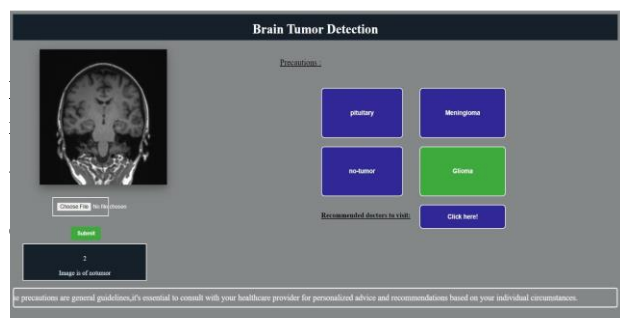
precision, recall, accuracy, and other metrics. This detailed analysis facilitates a deeper understanding of the model's advantages across different classes in binary or multiclass classification tasks.

VIII. EXPECTED RESULT :

The following points outline the obtained results, providing insights into our current outcomes and anticipated future developments.

1. Aiming for high accuracy in brain tumor detection using Convolutional Neural Network (CNN).
2. Enhancing user engagement with interactive web features, offering precautionary insights based on input scan results, and providing valuable information on potential risks and preventive measures.
3. Implementing federated learning to prioritize patient privacy while enhancing accuracy through a decentralized approach.
4. Developing a user-friendly web application for seamless MRI image upload and brain tumor detection.Implementing multi-class classification for various tumor types and ensuring interpretability of results for healthcare professionals. Enhancing efficiency to manage larger patient workloads and streamline the diagnostic process.



F
inal Output of the system

IX. CONCLUSION

In conclusion, this research has reached an important phase with the successful evolution of our predictive module, which demonstrated outstanding accuracy in scanning predictions across four inputs. Moving forward, our plan focuses on increasing user involvement through interactive web features that provide important insights into potential hazards and preventive steps. Furthermore, our dedication to enhancing healthcare includes pioneering federated learning, which ensures both accuracy and patient privacy. Our unwavering focus on innovation, user-centered design, and ethical considerations demonstrates our commitment to providing effective and ethical healthcare solutions.

REFERENCES

[1] *d. Saikat Islam Khan, Anichur Rahman. "Accurate brain tumor detection using deep convolutional neural network". https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9468505/*

[2] *Moinul Islam,Md. Tanzim Reza. "Effectiveness of Federated Learning and CNN Ensemble Architectures for Identifying Brain Tumors Using MRI".*

[3] *Imageshttps://link.springer.com/article/10.1007/s11063-022-11014-1#Sec32*

[4] *oheila Saeedi,Soraya. "MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques". Rezayi.https://bmcmedinformdecismak.biomedcentral.com/articles/10.1186/s12911-023-0211 4-6*

[5] *Manav Sharma, Pramanshu Sharma. "Brain Tumor detection using Machine learning". https://www.researchgate.net/publication/360224770_Brain_Tumour_Detection_Using_Mach in e_Learning*

[6] *Shreyash Ghosh, Sayeri Biswas, Jitsona De. "Automatic Brain Tumor Detection and Classification on MRI Images using Machine Learning Techniques". https://www.rcciit.org/students_projects/projects/ee/2020/GR15.pdf*

[7] *Divya Peketi, Vishnu Chalavadi, C Krishna Mohan, Yen WEi Chen, et al. "Automatic Brain Tumor Detection and Classification n MRI Images using Machine Learning Techniques".Published by Sayeri Biswas On behalf of RCC INSTITUTE OF INFORMATION TECHNOLOGY in 2020. https://ieeexplore.ieee.org/document/10191202.*

[8] *Khanh Le Dinh Veit, Khiem Le Ha, Trung Nguyen Quoc, Vinh Truong Hoang, et al.*

[9] *"MRI Brain Tumor Classification based on Federated Deep Learning". Published by KhanhLe Dinh Viet on behalf of the 2023 Zooming Innovation in Consumer Technologies Conference (ZINC). https://ieeexplore.ieee.org/document/10174015.*

[10] *Micah J. Sheller, G. Anthony Reina, Brandon Edwards, Jason Martin, and Spyridon*

[11] *Bakas et al "Multi-institutional Deep Learning Modeling Without Sharing Patient Data: A Feasibility Study on Brain Tumor Segmentation".Published by Micah J. Sheller on behalf of Center for Biomedical Image Computing and Analytics (CBICA), University of Pennsylvania, Philadelphia, PA, 19104, USA. doi: 10.1007/978-3-030-11723-8_9.*

[12] *https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6589345/*

[13] *M. Usman Akram, Anam Usman, et al. "Computer Aided System for Brain Tumor Detection and Segmentation". Published by M. Usman Akram on behalf of the International Conference on Computer Networks and Information Technology on 28 August 2022. https://ieeexplore.ieee.org/document/6020885*

[14] *Shubhangi Handore, Dhanashri Kokare, et al. "Performance Analysis of Various Methods of Tumor Detection".Published by Shubhangi Handore on behalf of the International Conference on Pervasive Computing (ICPC) on 16 April 2015.https://ieeexplore.ieee.org/document/7087002.*