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BRAIN TUMOR DETECTION USING CONVOLUTIONAL NEURAL NETWORK

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Abstract: This paper addresses the challenging task of brain tumor segmentation in 2D Magnetic Resonance Brain Images (MRI), recognizing the limitations of manual classification and the complexities arising from diverse tumor appearances. The comprehensive analysis employing traditional classifiers like Support Vector Machine, Multilayer Perceptron and a Convolutional Neural Network (CNN). The primary objective centers on distinguishing normal and abnormal pixels based on texture and statistical features. Notably, the CNN outperforms traditional classifiers, providing a robust foundation for accurate brain tumor segmentation. This research contributes significantly to advancing the field of medical image processing, offering a robust and efficient approach for brain tumor segmentation with room for further optimization.

Keywords: Brain tumor segmentation, Magnetic Resonance Imaging (MRI), Convolutional Neural Network (CNN), Traditional classifiers, Support Vector Machine (SVM), Multilayer perception.

I. INTRODUCTION

Medical imaging has revolutionized the field of healthcare by providing non-invasive methods to peer inside the human body, facilitating both diagnostic and treatment processes [1]. This diverse array of imaging techniques encompasses various modalities, each serving specific purposes in the quest for improved health outcomes. At the forefront of medical imaging, image segmentation emerges as a critical step in image processing, wielding significant influence over the success of subsequent stages [2]. In the realm of medical image processing, particularly in the detection of tumors or lesions, efficient machine vision and precise segmentation are paramount for accurate diagnosis and treatment planning.

Brain and other nervous system cancers pose a formidable health challenge globally, ranking as the 10th leading cause of death according to recent statistics [3]. The gravity of the situation is further emphasized by the World Health Organization's estimation that around 400,000 people worldwide are affected by brain tumors, resulting in 120,000 deaths annually [4]. In the United States alone, it is projected that approximately 86,970 new cases of primary malignant and non-malignant brain and Central Nervous System (CNS) tumors would be diagnosed in 2019 [5].

The urgency in addressing brain tumors stems from their potentially dire consequences. These abnormal cell formations within the brain manifest as either malignant or benign tumors. Malignant tumors, originating in the brain, exhibit aggressive growth and invasive tendencies, often spreading to other parts of the brain and impacting the central nervous system. On the other hand, benign tumors grow more slowly but can still pose significant health risks in the delicate environment of the brain.

Early detection of brain tumors holds immense significance in enhancing treatment possibilities and increasing the likelihood of survival. However, the manual segmentation of tumors or lesions is a laborious and time-consuming task, particularly given the sheer volume of Magnetic Resonance Imaging (MRI) images generated in routine medical practices [6]. MRI, being a preferred modality for brain tumor detection, presents challenges due to the ill-defined boundaries of tumors with soft tissues. Consequently, achieving accurate segmentation of tumors from MRI images becomes an extensive and intricate undertaking [6].

In this context, the development and integration of advanced technologies, particularly Computer-Aided Diagnostic (CAD) systems, play a pivotal role in addressing the challenges associated with brain tumor detection and segmentation [2]. These systems aim to enhance sensitivity and specificity in identifying tumors, thereby contributing to the overall efficacy of medical image processing.

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As we delve into the intricacies of brain tumor detection and segmentation, this paper explores the current landscape, challenges, and potential solutions to usher in a new era of improved diagnostics and treatment strategies. The overarching goal is to harness the power of medical imaging for the betterment of healthcare outcomes, particularly in the realm of brain tumor management.

II. LITERATURE SURVEY

A literature survey on brain tumor detection and segmentation using various image processing and machine learning techniques reveals a rich landscape of research aimed at improving diagnostic accuracy and efficiency. This survey synthesizes findings from a diverse array of studies, highlighting key methodologies, advancements, and challenges in this critical field.

In the realm of medical imaging, a comparative study by Kasban et al. [1] underscores the importance of different imaging modalities for brain tumor detection. Techniques such as MRI, as explored by Song et al. [8], offer multi-modality capabilities that enhance tumor segmentation accuracy. Moreover, advancements in segmentation algorithms, as discussed by Angamuthu Rajasekaran and Gounder [4], demonstrate the potential for more precise delineation of tumor boundaries.

Objective evaluation methods, as advocated by Surya Prabha and Satheesh Kumar [2], provide quantitative metrics for assessing segmentation performance. This is crucial given the complexity of brain tumor morphology and the need for reliable diagnostic tools. Additionally, the utilization of mathematical morphological reconstruction, as proposed by Devkota et al. [7], highlights innovative approaches to early- stage tumor detection.

Machine learning algorithms, including probabilistic neural networks (Badran et al. [9], Othman et al. [12]), support vector machines (Gupta and Singh [15]), and convolutional neural networks (Seetha and Raja [17]), have emerged as powerful tools for automated tumor classification and segmentation. These methods leverage large datasets to learn intricate patterns within MRI images, facilitating more accurate and efficient tumor detection.

Furthermore, hybrid approaches, such as fuzzy clustering combined with deformable models (Rajendran and Dhanasekaran [13]), demonstrate the potential for synergistic solutions that capitalize on the strengths of multiple techniques. Similarly, the integration of deep learning with type-specific image sorting (Sobhaninia et al. [14]) showcases innovative strategies for enhancing segmentation accuracy.

Despite these advancements, challenges persist in the field of brain tumor detection. Variability in tumor morphology, imaging artifacts, and the need for real- time processing present ongoing hurdles. Moreover, the interpretability of machine learning models and the generalizability of findings across diverse patient populations warrant further investigation.

In conclusion, the literature on brain tumor detection and segmentation reflects a dynamic landscape of research characterized by diverse methodologies and ongoing innovation. From traditional image processing techniques to cutting-edge machine learning algorithms, researchers continue to push the boundaries of diagnostic accuracy and efficiency. Moving forward, interdisciplinary collaboration and data-driven approaches will be paramount in addressing the remaining challenges and advancing the field toward improved patient outcomes.

III. METHODOLOGY

Modules:

- Data exploration: using this module we will load data into system
- Image processing: Using the module we will process of transforming an image into a digital form and performing certain operations to get some useful information from it.
- Splitting data into train & test: using this module data will be divided into train & test
- Model generation: Model building - Multilayer Perceptron - SVM - CNN. Algorithms accuracy is calculated.
- User signup & login: Using this module will get registration and login
- User input: Using this module will give input for prediction
- Prediction: final predicted displayed

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A) System Architecture

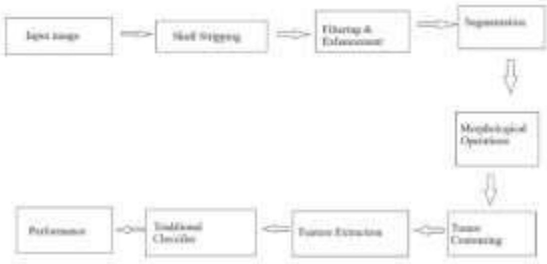

Fig 1: System Architecture

Proposed work

The proposed system aims to enhance the accuracy of brain tumor segmentation in 2D Magnetic Resonance Brain Images (MRI) by employing a multi-step approach. The study further advances to incorporate a Convolutional Neural Network (CNN) using Keras and Tensorflow, leveraging its capacity to capture intricate patterns in image data. The primary focus lies in distinguishing normal and abnormal pixels based on texture and statistical features, contributing to accurate brain tumor segmentation. This methodology provides a comprehensive and adaptive framework, accommodating diverse tumor sizes, shapes, and intensities..

B) Dataset Collection

Data collection for brain tumor detection using a Convolutional Neural Network (CNN) involves gathering a diverse set of medical imaging data, primarily consisting of brain MRI scans. These scans should encompass various types of brain tumors, including gliomas, meningiomas, and pituitary adenomas, along with normal brain images for comparison. Additionally, metadata such as patient demographics, tumor characteristics, and clinical outcomes should be collected to enrich the dataset and facilitate comprehensive analysis. Efforts should be made to ensure the data's quality, including image resolution, consistency in imaging protocols, and accurate tumor annotations by experienced radiologists or clinicians. Collaborating with healthcare institutions or research organizations to access their databases can significantly augment the dataset's size and diversity. Moreover, ensuring compliance with data privacy regulations such as HIPAA is paramount to protect patient confidentiality and adhere to ethical standards. Establishing data sharing agreements and obtaining necessary approvals from institutional review boards (IRBs) are crucial steps in the data collection process. Furthermore, augmenting the dataset with synthetic data or data augmentation techniques can enhance the model's robustness and generalization capabilities. Overall, meticulous data collection is foundational for developing an effective CNN-based brain tumor detection system with high accuracy and clinical relevance.

C) Pre-processing

Preprocessing for brain tumor detection using a Convolutional Neural Network (CNN) involves several crucial steps to ensure the effectiveness of the model. Firstly, data exploration is essential, where MRI images are loaded into the system. This step involves understanding the structure and characteristics of the dataset, such as image dimensions, pixel intensity range, and class distribution. Following data exploration, image processing techniques are applied to transform the raw MRI images into a suitable digital format. This includes operations like resizing, normalization, and noise reduction to enhance the quality and consistency of the images. Additionally, feature extraction methods may be employed to extract relevant information from the images, such as texture features or edge detection. Once the images are preprocessed, the dataset is split into training and testing sets to evaluate the performance of the model. This ensures that the model's ability to generalize to unseen data is properly assessed. Furthermore, user signup and login functionalities are implemented to manage user interactions with the system. Users can input MRI images for prediction, which undergo the same preprocessing steps before being fed into the CNN model. Finally, the model generates predictions, indicating the presence or absence of a brain tumor based on the preprocessed images. Overall, robust preprocessing is crucial for optimizing the CNN model's performance in accurately detecting brain tumors from MRI scans.

D) Training & Testing

In the process of training and testing a brain tumor detection system using a Convolutional Neural Network (CNN), several key steps are involved. Firstly, the data exploration phase involves loading the dataset, which typically consists of MRI images of the brain, into the system. This step ensures that the dataset is properly formatted and ready for further processing.

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Next, image processing techniques are applied to transform the MRI images into a digital form and extract useful information from them. This involves preprocessing steps such as normalization and augmentation to enhance the quality and diversity of the dataset.

After preprocessing, the dataset is split into training and testing sets using a module dedicated to this task. The training set is used to train the CNN model, while the testing set is used to evaluate its performance and generalization ability.

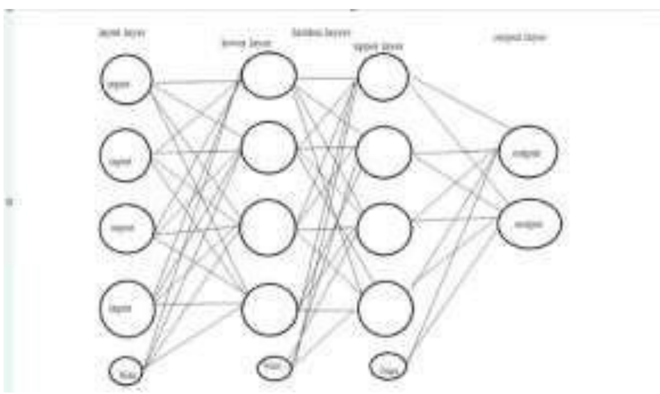
In the model generation phase, various machine learning algorithms including Multilayer Perception, SVM and a CNN are implemented and their accuracies are calculated. This step helps in selecting the best- performing model for the task of brain tumor detection.

Additionally, user signup and login functionalities are implemented to ensure secure access to the system. Users can input MRI images for prediction through a user input module, and the final predictions are displayed based on the selected model. This comprehensive approach ensures an efficient and accurate brain tumor detection system using CNN technology.

E) Algorithms.

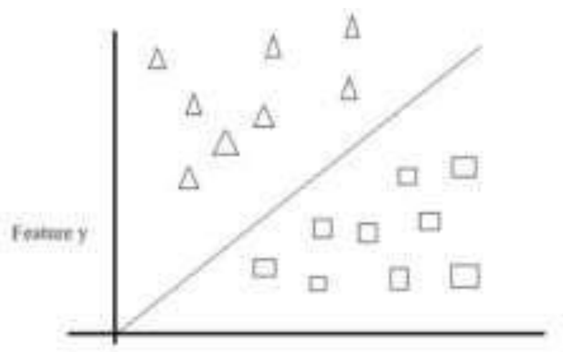
Multilayer Perceptron:

Multilayer Perceptron is a type of artificial neural network with multiple layers of nodes. It uses backpropagation for training and is capable of learning complex patterns. MLP is utilized for its capacity to capture intricate patterns in image data, contributing to the project's goal of accurate brain tumor segmentation through diverse methodologies.



Support Vector Machine (SVM):

SVM finds a hyperplane that best separates data points into different classes, maximizing the margin between classes. SVM is chosen for its effectiveness in classifying tumor regions with varying characteristics, contributing to the diverse set of classifiers for comprehensive brain tumor segmentation.



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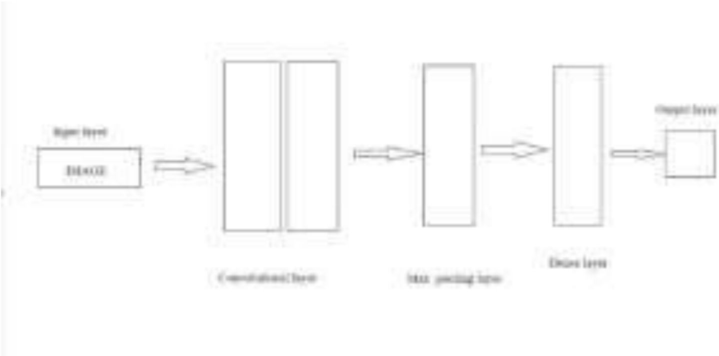
Convolutional Neural Network (CNN):

CNN is a deep learning algorithm designed for image analysis, featuring convolutional layers that automatically learn hierarchical representations of image features. CNN is implemented for its ability to capture intricate patterns in 2D MRI images contributing to improved segmentation accuracy in the project's goal of brain tumor detection.



IV. EXPERIMENTAL RESULTS

A) Comparison Graphs → Accuracy, Precision, Recall, f1 score

Accuracy: A test's accuracy is defined as its ability to recognize debilitated and solid examples precisely. To quantify a test's exactness, we should register the negligible part of genuine positive and genuine adverse outcomes in completely examined cases. This might be communicated numerically as:

Accuracy = TP + TN TP + TN + FP + FN.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

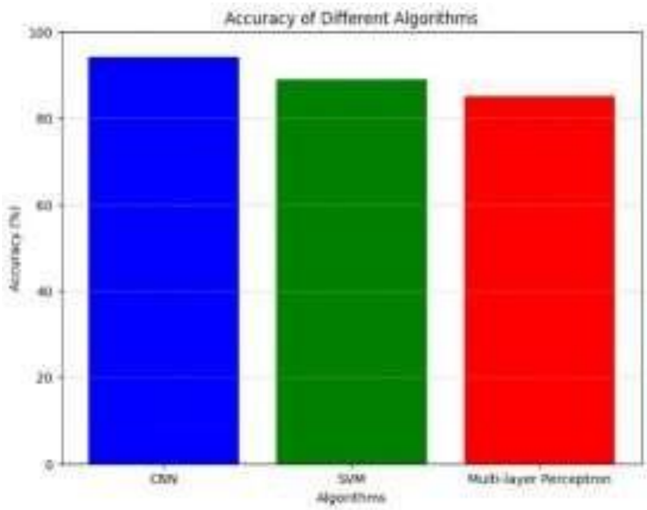


Fig 2: Accuracy Graph

Precision: Precision measures the proportion of properly categorized occurrences or samples among the positives. As a result, the accuracy may be calculated using the following formula:

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Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

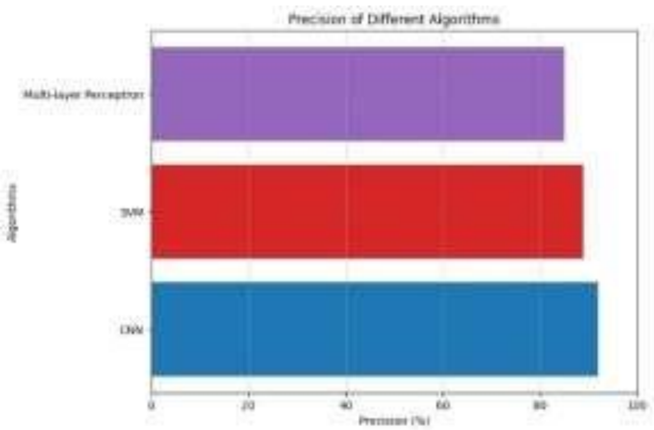

Fig 3: Precision Score Graph

Recall: Recall is a machine learning metric that surveys a model's capacity to recognize all pertinent examples of a particular class. It is the proportion of appropriately anticipated positive perceptions to add up to real up-sides, which gives data about a model's capacity to catch instances of a specific class.

$$Recall = \frac{TP}{TP + FN}$$

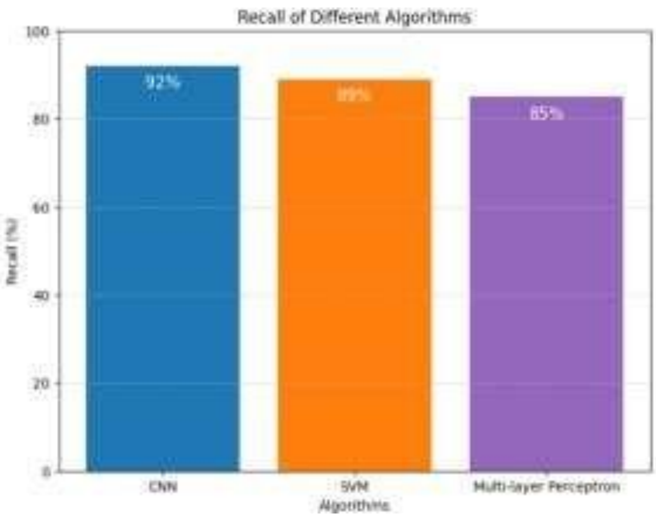

Fig 4: Recall Score Graph

F1-Score: The F1 score is a machine learning evaluation measurement that evaluates the precision of a model. It consolidates a model's precision and review scores. The precision measurement computes how often a model anticipated accurately over the full dataset.

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$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

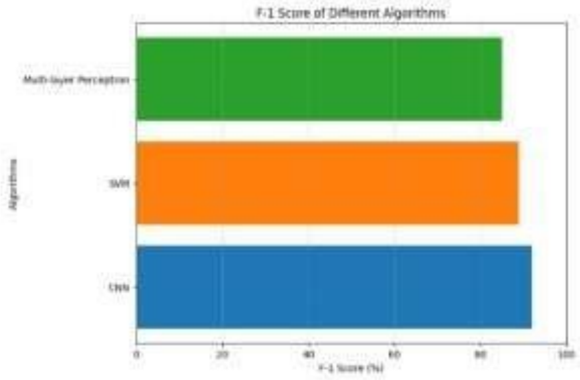

Fig 5: F1 Score Graph

V. CONCLUSION

In conclusion, the proposed system for brain tumor segmentation in 2D MRI images presents a comprehensive and adaptive framework that addresses the challenges posed by diverse tumor appearances. The combination of traditional classifiers, including Support Vector Machine, Multilayer Perceptron, demonstrates a robust methodology for accurate tumor region analysis. The subsequent integration of a Convolutional Neural Network (CNN) using Keras and Tensorflow enhances the system's ability to capture intricate patterns in image data, achieving notable training accuracy of 97% and test accuracy of 94%.

This highlights the adaptability and effectiveness of the proposed system in accommodating diverse tumor characteristics. The findings underscore the potential for a hybrid approach, combining the strengths of traditional classifiers and deep learning, to achieve enhanced accuracy and reliability in brain tumor segmentation tasks. Future research may continue to explore innovative techniques for continual improvement in medical image processing applications.

VI. FUTURE SCOPE

The future scope of this research involves continuous advancements in brain tumor segmentation through the exploration of emerging technologies such as advanced deep learning architectures, improved feature extraction methods, and the integration of multimodal imaging data. Further research could focus on enhancing real-time processing capabilities, increasing the dataset diversity, and collaborating with healthcare professionals to facilitate the integration of the proposed system into clinical practice, ultimately contributing to more accurate and efficient diagnosis and treatment planning for patients with brain tumors.

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