Brain Tumor Detection Using CNN-GoogleNet With LSTM

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Abstract—**Analyzing brain tumors with no human intervention is considered as a vital area of research. However, this can be achieved using Convolutional Neural Networks (CNNs) and Hybrid algorithm (GoogleNet and LSTM). They have performed exceptionally well in solving computer vision problems and many others such as visual object recognition, detection, and segmentation. It is used in detecting brain tumors by optimizing the brain images using segmentation algorithms which are highly resilient towards noise and cluster size sensitivity problems with automatic region of Interest (ROI) detection. One of the main reasons for choosing CNN and Hybrid algorithm is due to its high accuracy and it is not necessary to perform manual feature extraction in these networks. It is not an easy task to detect the brain tumor and accurately identify the type. CCN and HYBRID algorithm (GoogleNet with LSTM) performance is better than others because of its wide usage in recognizing images. Brain Tumor segmentation is one of the most crucial and arduous tasks in the terrain of medical image processing as a human-assisted manual classification can result in inaccurate prediction and diagnosis. Moreover, it is an aggravating task when there is a large amount of data present to be assisted. Brain tumors have high diversity in appearance and there is a similarity between tumor and normal tissues and thus the extraction of tumor regions from images becomes unyielding.**

Keywords—Convolutional Neural Networks, Brain Tumor, Hybrid Algorithm (GoogleNet with LSTM)

I. INTRODUCTION

A branch of AI called deep learning has shown amazing promise in several fields, including medical imaging. Convolutional Neural Networks (CNNs) and Hybrid methods (using GoogleNet with LSTM) have become popular techniques in the field of brain tumor identification and classification. CNNs and hybrid algorithms are very good at identifying malignancies in MRI scans because they can automatically learn and adapt spatial hierarchies of features from input pictures. Their proficiency in managing the intricacy and fluctuations of medical images aids in the precise identification of tumors. The combination of LSTM's sequential data processing capability and GoogleNet's deep architecture and effective feature extraction considerably improves the efficiency of these techniques.

Researchers want to enhance patient outcomes and treatment planning by utilizing CNNs and Hybrid models to increase brain tumor detection accuracy and dependability. Oncology and medical imaging could advance greatly because of this combination of deep learning algorithms.

Today we live in an era where diseases are increasing day by day and there is a necessity to develop the quality of treatment. The tumor is an irregular lump on any body part and is considered one of the dangerous diseases. Out of all the tumors, brain tumor is the fatal one that can occur in any part of the brain. It is mainly defined as abnormal growth of cells within the brain. These abnormal cells can affect healthy brain cells which in turn results in malfunctioning of the brain. A brain tumor can be classified into different types. These tumors can either be Malignant (cancerous) or Benign (non-cancerous). It is not an easy task to detect the brain tumor and accurately identify the type. CNN and Hybrid models' performance is better than others because of their wide usage in recognizing images. It is basically a group of neurons and has learnable weights. Besides this, they are known for high accuracy and performance. The observation from Human in predicting the tumor may mislead due to the noise and distortions found in the image. This motivates our work in constructing the algorithm to predict the tumor. This includes the method of detecting the tumor and classifying them (i.e., either tumorous or non-tumorous).

Convolutional neural networks (CNN) and hybrid models are the main methods used in the Deep Learning scope of brain tumor detection. CNNs are very good at identifying images, and they can analyze brain scans to determine the location, size, and existence of tumors. In the end, this integration of hybrid models could improve patient prognosis and healthcare efficiency by increasing diagnostic accuracy, decreasing detection time, and personalizing treatment strategies.

Deep Learning's incorporation into brain tumor diagnosis transforms medical imaging by increasing speed and accuracy. In order to determine the existence and characteristics of tumors in MRI scans, Convolutional Neural Networks (CNN) and Hybrid algorithms are used in image recognition. To ensure accurate diagnosis, further identify and differentiate tumor kinds. In the diagnosis of brain tumors, the combination of CNN and the Hybrid Algorithm (LSTM with GoogleNet) not only helps physicians make well-informed judgments, but also opens the door to individualized treatment regimens that will eventually improve patient outcomes and quality of life.

Creating and testing a strong deep learning-based system for the precise identification and categorization of brain cancers from MRI scans is the main goal of this project. In addition to hybrid models GoogleNet with LSTM, the system incorporates Convolutional Neural Networks (CNN) for feature extraction, picture segmentation, and classification. Enhancing diagnosis precision, cutting down on the amount of time needed for manual image processing, and giving clinicians a trustworthy tool to use when making treatment decisions for brain tumors are the three main goals.

II. Literature Review

According to [1] N.K. Ahmedzai, S. Bergman, B. Bullinger, M. Cull, A. Duez, N.J. Filiberti, A. Flechtner, H. Fleishman, S.B. & de Haes, J.C. (1993), the average time required to complete the questionnaire was approximately 11 minutes, and most patients required no assistance. The data supported the hypothesized scale structure of the questionnaire except for role functioning (work and household activities), which was also the only multi-item scale that failed to meet the minimal standards for reliability (Cronbach's alpha coefficient > or = .70) either before or during treatment. Validity was shown by three findings. First, while all interscale correlations were statistically significant, the correlation was moderate, indicating that the scales were assessing distinct components of the quality-of-life construct. Second, most of the functional and symptom measures discriminated clearly between patients differing in clinical status as defined by the Eastern Cooperative Oncology Group performance status scale, weight loss, and treatment toxicity. Third, there were statistically significant changes, in the expected direction, in physical and role functioning, global quality of life, fatigue, and nausea and vomiting, for patients whose performance status had improved or worsened during treatment. The reliability and validity of the questionnaire were highly consistent across the three language-cultural groups studied: patients from English-speaking countries, Northern Europe, and Southern Europe.

According to [2] Chithambaram, T. and Perumal, K., 2017, Automatic faults detection in MR images is very significant in many symptomatic and cure applications. Because of high quantity data in MR images and blurred boundaries, tumor segmentation and classification are very hard. This work has introduced one automatic brain tumor detection method to increase the precision and yield, however it decreases the diagnosis time. The goal is to classify the tissues into two classes of normal and abnormal. The proposed method can be used successfully and applied to detect the contour of the tumor and its geometrical dimensions. Furthermore, based on discovering vector quantization with that image and data analysis although a manipulation technique is aimed to carry out an automated brain tumor classification using MRI-scans. The assessment of the changed ANN classifier execution is measured in price of the training execution, classification accuracies and computational time. MRI brain tumor images detection is a difficult task due to the variance and complexity of tumors. This research presents two techniques for the detection purpose; the first one is Edge detection and segmentation instant is Artificial Neural Network proficiency. The aimed Neural Network technique comprises of some stages, namely, feature extraction, dimensionality reduction, detection, segmentation, and classification. In this research, the proposed method is more accurate and effective for brain tumor detection and segmentation. For the implementation of this proposed work, we use the Image Processing Toolbox below MatLab.

According to [3] Kavitha AR, Chitra L, kanaga R**.,** Deep Learning is a new machine learning field that gained a lot of interest over the past few years. It was widely applied to several applications and proven to be a powerful machine learning tool for many of the complex problems. In this paper we used Deep Neural Network classifier which is one of the DL architectures for classifying a dataset of 66 brain MRIs into 4 classes e.g. normal, glioblastoma, sarcoma and metastatic bronchogenic carcinoma tumors. The classifier was combined with the discrete wavelet transform (DWT), the powerful feature extraction tool and principal components analysis (PCA) and the evaluation of the performance was quite good over all the performance measures.

According to [4] A.P. Zafar, S.Y. Uronis, H. Wheeler, J.L. Coan, A. Rowe, K. Shelby, R.A. Fowler, R. & Herndon, J.E., 2nd. (2010), this study utilized a prospectively collected dataset of ePROs from oncology clinics that administered the Patient Care Monitor 2.0 (PCM), a validated symptoms survey assessing 78 items for men, and 86 for women. We tabulated the frequency of missing items, by item and domain (emotional, functional, and physical symptom-related), and examined these by age, gender, education, race and marital status. Within 20,986 encounters, there were responses to at least 1 PCM item from 6933 unique patients. The highest frequency of missing answers occurred for: “attend a paid job” (10.7%), “reduced sexual enjoyment” (3.8%), and “run” (3.7%). By domain, 12.3% of functional, 8.4% of physical symptom-related, and 1.6% of emotional constructs contained at least one missing item. For functional and physical symptom-related items, missingness was most common in patients >60 years old.

According to [5] N.K. (2003**), A** diagnosis of cancer typically results in patients experiencing uncertainty about and loss of control over their situation, which in turn has a negative influence on their health outcomes. Cancer treatment further disrupts patients' quality of life. Throughout their cancer journey patients often rely on their physicians to provide them with social/interpersonal, informational, and decisional support. A growing body of research shows that physicians' communication behaviour does indeed have a positive impact on patient health outcomes. Thus, the patient-physician interaction assumes great significance in the cancer care delivery process. It is encouraging to note that research in this area, largely dominated by studies conducted in primary care, is attracting the attention of cancer researchers. To encourage and aid future research on patient-physician communication in cancer care, this paper presents a critical evaluation of existing literature on key elements of physicians' communication behaviour (i.e., interpersonal communication, information exchange, and facilitation of patient involvement in decision-making). Different approaches to assessing physician behaviour are discussed followed by a review of key findings linking physician behaviour with cancer patient health outcomes. Finally, potential limitations of existing research are highlighted and areas for future research are identified.

III. Proposed Methodology

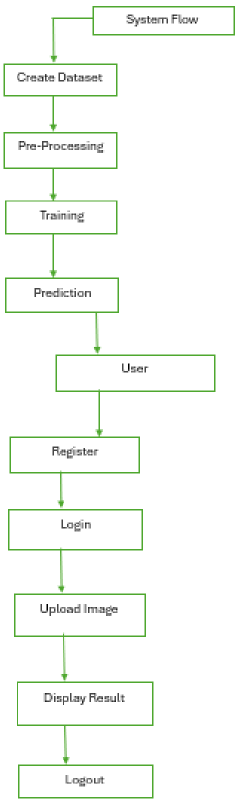

Fig. III-1 Workflow of Proposed System

A. *LSTM (Long Short-Term Memory):*

- LSTM is a type of recurrent neural network (RNN) architecture designed to address the vanishing gradient problem in traditional RNNs, making it capable of learning long-term dependencies in sequential data.
- In the context of medical image analysis, LSTM networks can be used to capture temporal dependencies or sequential patterns within the data.
- In the brain tumor detection project, LSTM could potentially be used for tasks such as analysing sequences of medical images over time (e.g., tracking tumor growth or changes in tumor characteristics) or processing sequential data from different imaging modalities.

B. *GoogleNet*:

- GoogleNet, also known as InceptionV1, is a convolutional neural network architecture designed by Google. It is known for its deep architecture with efficient use of computational resources with inception modules.
- In the context of the brain tumor detection project, GoogleNet can be used for feature extraction from medical images. Its deep architecture allows it to capture complex patterns and structures within the images effectively.

C. *Hybrid Algorithm (GoogleNet with LSTM)*

The hybrid algorithm combines LSTM and GoogleNet to utilize the strengths of both architectures. GoogleNet is employed for feature extraction from medical images due to its ability to capture intricate details and patterns. LSTM is utilized to capture any temporal dependencies or sequential patterns in the data, enhancing the model's ability to analyse sequences of medical images or data from different imaging modalities over time.

By combining GoogleNet and LSTM, the hybrid algorithm aims to achieve high accuracy in brain tumor detection and segmentation while minimizing manual intervention and addressing challenges such as noise sensitivity and cluster size issues.

In the project, the hybrid algorithm likely involves using GoogleNet for initial feature extraction from brain images and then feeding these features into LSTM networks for further analysis, potentially incorporating temporal information or sequential patterns if applicable.

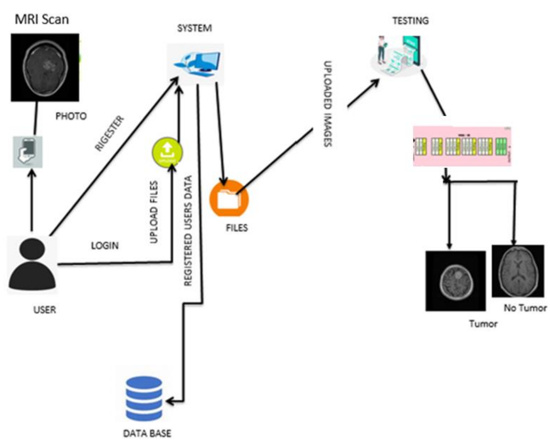

Fig. III-2 Model Architecture

1) *System*

Create Dataset: Here we have taken the brain Tumor diseases image dataset from kaggel.com, the data set is split into two categories one is training and another one is testing.

Pre-processing: Resizing, Gray scaling and reshaping the images into appropriate format to train our model. The final dataset is split into training and testing dataset with test size of 10%.

Training: Use the pre-processed training dataset to train our model using Hybrid algorithm.

2) *User*

Register: The user needs to register, and the data stored in MySQL database.

About-Project: In this application, we have successfully created an application which takes to classify the brain images.

Login: A registered user can login using the valid credentials to the website to use an application.

Upload Image: The user must upload an image which needs to be tested for Brain Tumor.

Prediction: The results of our model are displayed as Tumor, and No Tumor.

Logout: Once the prediction is over, the user can log out of the application.

IV. RESULTS

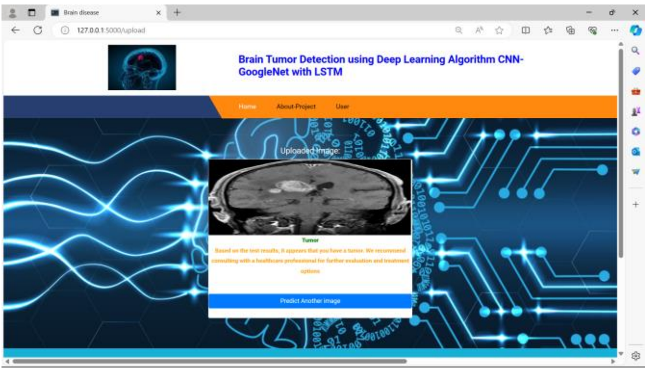

Fig. IV-1 Image having Tumor

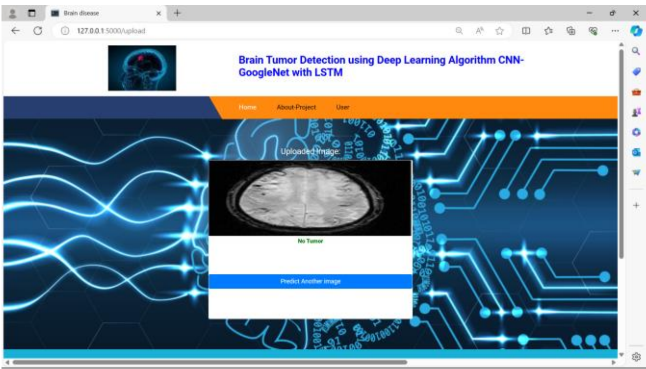

Fig. IV-2 Image without Tumor

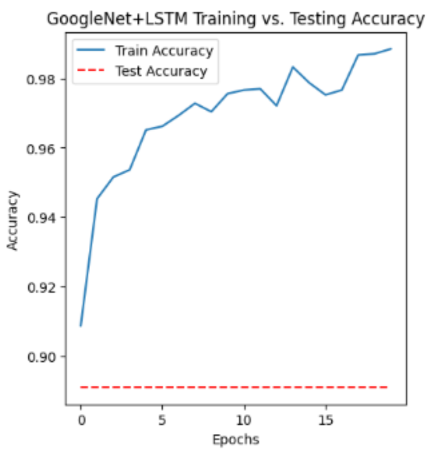

Fig. IV-3 Training and Testing Accuracy

V. CONCLUSION

In the medical field, manual identification of brain tumor by doctors referring the MRI images is a very time-consuming task and can be inappropriate for a large amount of data. Instead of manual identification, image processing and machine learning techniques can be used to identify the tumor from the images.

Therefore, this model helps in understanding the creation of a system that will carry out image processing and identify the Brain Tumor using a deep learning approach.

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