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A Hybrid Deep Learning and Machine Learning Framework for Enhanced Brain Tumor Detection in MRI Using MobileNetV3 Features

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Abstract- — This study demonstrate the hybrid framework model that combine Machine Learning (ML) and Deep Learning (DL) techniques for the detection of brain tumor on MRI scan dataset. We employ MobileNetV3 for deep feature extraction via transfer learning, followed by classification using Logistic Regression (LR), SVM, Random Forest, KNN, and XGBoost. Experimental results demonstrate that Logistic Regression paired with MobileNet features achieved superior performance (Accuracy: 95.02%, Precision: 94.78%, Recall: 94.53%, F1-score: 94.58%), outperforming more complex classifiers. This indicates that MobileNet-derived features create a nearly linearly separable representation, positioning LR as an efficient and effective tool for automated, accurate brain tumor diagnosis, thereby augmenting clinical decision-making.

Keywords: Brain tumor detection, MRI classification, MobileNet, Transfer learning, Logistic Regression, Hybrid AI framework.

I. INTRODUCTION

Brain tumors (BT) is refer to the irregular and excessive multiplication of cells within the intracranial space or central spinal canal remain a formidable source of mortality and morbidity across all age groups. These lesions disrupt the delicate architecture of the brain. Benign tumors which are typically slow-growing and localized and malignant tumors which are invasive aggressive and capable of spreading. A further critical distinction is made between tumors that originate within the brain itself (primary tumors) and those that travel to the brain from other sites in the body (metastatic or secondary tumors) with the latter being more common in adults.

The symptoms a patient experiences are a direct reflection of the tumor's location and its disruptive impact. Common presentations include persistent and worsening headaches, new-onset seizures, and progressive neurological deficits such as weakness, vision problems and speech difficulties. Perhaps more insidiously tumors can also alter a person's cognitive abilities, behavior and personality. For decades the standard of care has relied on the expert yet inherently subjective visual analysis of these scans by radiologists and neurologists. This traditional method while invaluable carries limitations. Diagnostic accuracy can vary between observers and is influenced by individual experience and the subtle often ambiguous and features of early-stage tumors. The complexity and volume of imaging data can also challenge even the most seasoned specialist potentially leading to diagnostic delays.

This landscape is now being transformed by the integration of Artificial Intelligence (AI) specifically through ML and DL. Unlike rule-based computer programs these systems learn directly from vast libraries of historical medical images. By identifying complex multidimensional patterns within the data they can assist in detecting tumors precisely outlining their boundaries and suggesting classifications with remarkable speed and consistency. This model helps the medical practitioners to take their decision effectively and accurately. It acts as a powerful second reader highlighting areas of concern quantifying features invisible to the human eye and helping to standardize assessments. The promise is a future where diagnostic decisions are more timely, accurate, and reproducible.

Managing brain tumors is a high-stakes endeavor in modern medicine. The path forward lies not in abandoning the critical judgment of medical professionals but in empowering them with sophisticated computational tools. The synergy between human clinical insight and artificial intelligence offers a compelling new paradigm to improve patient outcomes guiding more confident therapeutic decisions from earlier in the diagnostic pathway.

In this work hybrid computational approach is used to improve automatic identification of brain tumors in MRI scan images.Our approach strategically integrates the representational power of DL with the robust classification capabilities of traditional ML algorithms.

In this study two phase process forms the foundation of proposed methodology. In the first phase deep feature extraction is performed on MRI scan images using transfer learning MobileNet Model.These extracted feature vectors which encode high-level visual patterns indicative of pathology. These extracted features passed to the ML model for the classification.

We evaluate several classifiers to determine the most effective pairing including LR, Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), and XGBoost.

In this section we discussed the introduction of the paper. In the second section we will discuss literature survey. In the third section we will discuss methods and material and in the last section we will discuss about result and discussion of the paper.

II. LITERATURE SURVEY

Novsheena Rasool and others implemented ML and DL techniques. They used DL techniques such as CNN, VGG16, ResNet50, and hybrid models. They used publicly available dataset such as BraTS and Figshare for train the models. In the initial stage they performed image pre-processing and augmentation. The hybrid DL model achieved highest accuracy of 95%. This DL model has a capacity to capture spatial and textural MRI features, reducing diagnostic delays and enhancing clinical decision-making [1]. Rita Appiah and others addresses the growing requirement for efficient means of detecting brain tumors by comparing a low-order model Proper Orthogonal Decomposition (POD) integrated with a CNN, against standard DL models. The methodologies implement POD-CNN and model can be executed on lower computational power.

This model achieved 95.88% accuracy with one-third the computational time as compared with CNN [2]. T. Lakshmi Prasanthi and others conduct the comparative analysis of advanced DL model such as DenseNet121, EfficientNetB7, InceptionResNetV2, InceptionV3, ResNet50V2, VGG16, VGG19 for classification of MRI images. They implemented hybrid CNN model with precision of 96.63%. Results indicate VGG19 and InceptionResNetV2 show effectiveness in detecting glioma tumors. The proposed hybrid model demonstrates higher performance and reliability and demonstrating the benefits of a multi-framework DL approach for improving both the correctness and promptness of brain tumor detection [3]. In a study by Mohammed and colleagues a CNN was developed using a dataset of 4,000 MRI scans. All images were resized to 224 × 224 pixels prior to processing. The model attained a classification accuracy of 97.28%, highlighting the capability of DL in identifying brain tumors. The findings further indicated that increasing the dataset size enhances the model's ability to generalize. The network was trained over 60 epochs to boost its predictive performance.

Overall, the results demonstrated that the DL approach outperforms conventional methods in both precision and processing speed [4]. An investigation by Anantharajan and colleagues introduced a hybrid model combining DL and ML techniques for brain tumor detection. In their approach MRI scans underwent preprocessing through an Adaptive Contrast Enhancement Algorithm (ACEA) followed by a median filter to enhance image clarity. Segmentation was carried out using Fuzzy C Means clustering after which texture features including energy, mean, entropy, and contrast were extracted via the Gray-Level Co-occurrence Matrix (GLCM). For classification of healthy versus abnormal brain tissues, the researchers employed an Ensemble Deep Neural Support Vector Machine (EDN-SVM) classifier.

The model was developed using publicly accessible MRI datasets. Experimental results showed that the proposed system attained an accuracy of 97.93%, along with a sensitivity of 92% and a specificity of 98%. [5]. Sandeep Kumar Mathivanan and others implemented transfer learning model such as ResNet152, VGG19, DenseNet169, and MobileNetv3 classification for brain tumor for MRI images. They used five-fold cross validation and image enhancement technique for the MRI images. The MobileNetv3 is achieved highest accuracy with 99.75%. But this not demonstrate the generalization across diverse dataset [6].

In a study by Ramtekkar and his team, an optimized approach was developed for the accurate identification of brain tumors from MRI scans. To reduce noise artifacts several preprocessing filters were applied, including Gaussian, mean, and median filters. Following preprocessing, texture features were extracted using the GLCM. The model's feature selection capability was then strengthened through the application of multiple optimization algorithms: Ant Colony Optimization, Bee Colony Optimization, Particle Swarm Optimization, Genetic Algorithm, Gray Wolf Optimization, and Whale Optimization Algorithm. A customized CNN was subsequently used for classification. This optimized system achieved a detection accuracy of 98.9%. [7].

Shyo Prakash Jakhar and others proposes DL based segmentation technique for BT detection using Multi scale Fractal Feature Network (MFFN). In this proposed methodology they used pixel level segmentation combined with fractal residual learning and multi-scale feature extraction to enhance sensitivity and accuracy. Multi-level segmentation helps preserve tumor information while minimizing false regions so it improves accuracy of the models. The model was evaluated using the Cancer Imaging Archive (TCIA) dataset and validated through 5-fold cross-validation. Experimental results showed a segmentation accuracy of 94.66%, sensitivity of 94.42%, and specificity of 92.81% [8]. D. S. Wankhede and others uses MRI images for predicting the glioblastoma of brain tumors. The authors were collected MRI images from the hospital. This images is pre-processed by subtracting mean intensity value and standard deviation of the brain region. The noise from the images were reduced by using bilateral filters. The tumor region of the images automatically segmented using Modified Fuzzy C Means Clustering (MFCM). They find out significant features and differentiated between high grade and low grade form GBM. The authors proposed Multilevel Layer modelling in Faster R-CNN (MLL-CNN) for the model [9].

The authors used dataset of 3,264 MRI brain images to build the model. The images consist of glioma, meningioma, pituitary tumors and healthy images. They apply image augmentation techniques to the dataset for more generalise the dataset. The authors developed 2D CNN with eight convolutional layers and four pooling layers and convolutional auto-encoder network combining encoding and classification. 2D CNN achieved accuracy of 96.47% and 95% for recall, while the auto-encoder reached 95.63% accuracy [10]. Kamini Lamba and others used publicly available MRI dataset for train the model. They performed data augmentation technique for standardize and expand the dataset, followed by transfer learning using a VGG-16 architecture to extract deep spatial features. To enhance the classification performance they used linear SVM. The experimental result shows that with VGG16 architecture they get 98.87% for accuracy, 99.09% for precision, 98.73% for recall, 99.02% for specificity, and 98.91% for F1-score [11].

The researchers developed a sequential deep learning model to detect and classify brain tumors from MRI scans. The process was divided into two phases. Initially, the model differentiated between neoplastic (tumor-bearing) and non-neoplastic (healthy) brain tissue. Subsequently, it carried out the classification of medical images in the second stage. The authors implemented classification model by using four optimizers such as Adam, Nesterov Momentum, RMSProp, and Adagrad. Adam performed best at distinguishing tumor from non-tumor brains, with 100 % training accuracy and 98 % validation and test accuracy. Nesterov Momentum performed best at differentiating the three tumor types, with 100 % training accuracy and 92 % validation and testing accuracy. Nesterov also performed best on the third classification task, with 100 % training accuracy and 95 % validation and test accuracy [12]. The authors proposed DL model IRNetv for BT identification using CNN. This architecture integrates inception modules and residual connections to extract diversified features from MRI images using varying convolutional filters and kernel sizes. Two publicly available MRI dataset of 4600 images and 253 brain images were used. Three optimizer such as Adam, RMSProp, SGD were used with batch size of 16, 32, 64. Adam optimizer with a batch size of 64 shows the best performance. The proposed IRNetv model achieved accuracy of 99% for classification [13].

In a study by Priya and colleagues, a hybrid deep learning architecture was introduced that integrates AlexNet with Gated Recurrent Unit (GRU) networks to classify brain tumors from MRI data. Prior to model training, image preprocessing was carried out using a non-local means filter. Within this framework, AlexNet serves to extract spatial features via its convolutional layers, while the GRU component manages sequential dependencies and helps resolve the issue of vanishing gradients. To improve generalization and reduce the risk of overfitting, hyperparameter tuning was applied. The model categorizes brain MRI scans into four distinct classes: glioma, meningioma, pituitary tumor, and normal. The proposed hybrid system achieved an accuracy of 97%, along with a precision of 97.63%, a recall of 96.78%, and an F1-score of 97.25% [14]. Kavita A and others introduces brain tumor detection technique that combine digital twins, IoT-based cloud storage, and advanced machine learning techniques. This digital twins enable device is capture MRI images and stored this images centrally using IoT systems. The feature selection is performed using PSO. The extracted feature are classified using CNN, SVM and Extreme Learning Machines (ELM). The study highlights the efficiency of CNN in detecting abnormal tissues within MRI scans [15].

III. METHODS AND MATERIALS

In this research on brain tumor prediction in MRI image with the help of Deep learning, extensive datasets on both healthy and diseased MRI images were obtained on online kaggle repository. We divided a total 7000 MRI images into the train folder and test folder and 80% of the images were used to

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train the model and 20% of the images were used to test the model. This dataset is designed for multi-class classification tasks and is suitable for model training utilizing transfer learning approaches.This set of data is separated in training and testing of the model that guarantee the impartial evaluation of the model and will avoid the overfitting of the model.

Flow of algorithm

Step 1: Image pre-processing using image resizing and augmentation.

All raw MRI images I ϵ RH X W were resized to the same size first, and artificially expand the training dataset and improve the model's ability to generalize a data augmentation technique was applied..

Step 2: In this step perform the feature extraction using transfer learning techniques such as MobileNet-V3.

Fmobilenet(I) denote the extracted feature vectors:

Xm= Fmobilenet(Ihe) ϵ Rd

The final feature vector is x= [Xr; Xm] ϵ Rd

Step 3: The features extracted in the steps 1 and above are fed into the machine learning model like LR, SVM, RF, KNN and XGBoost. This step consists of training the model with machine learning algorithms.

Step 4: this step involves the model validation methods like accuracy, precision, recall and F1-score.

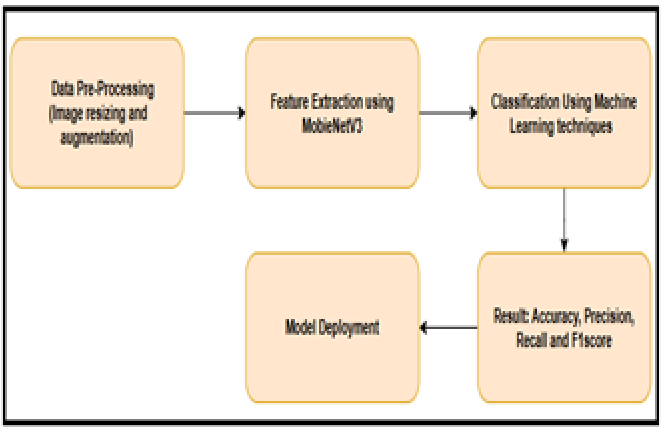

Figure 01: Proposed Methodology

The above figure 1 is a detailed pipeline of the deep learning approach to detect brain tumors, the first step of which is the essential data pre-processing where medical images are usually downsized to common sizes and images are augmented by image-processing methods such as rotation or flipping to increase the diversity of the dataset and the robustness of the model. The system is built around a compact yet efficient CNN, such as MobileNetV3, which extracts features with low computational cost. This enables the detection of tumors by identifying key textural and structural patterns without requiring substantial processing power. This features are then introduced into the traditional ML classifiers like LR, RF, SVM, KNN and XGBoost to enable specific tumor classification into categories (i.e.: malignant or benign). Upon training, the improved model is implemented in clinical or mobile settings where it can be easily accessed and provided with real time diagnostic assistance. Lastly performance is strictly assessed with the use of measurements such as accuracy, precision, recall, and F1 score to ensure that the model is reliable and clinically relevant with a balance between efficiency and diagnostic accuracy to make it effective in actual medical practice.

IV. RESULT AND DISCUSSION

In this study, a deep learning approach specifically a form of transfer learning was used for feature extraction, and the extracted features were subsequently applied to the classification task. The testing was conducted in Python programming language on the Google Colab platform with a T4 graphic card. The primary objective of this study is to evaluate the performance of the proposed model.

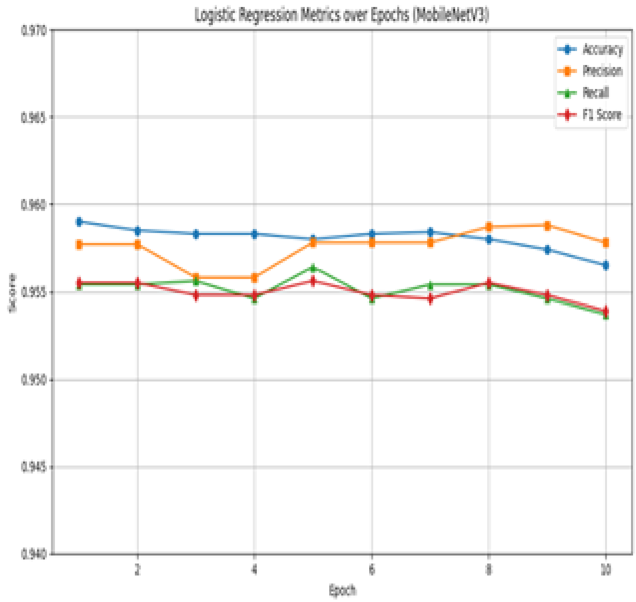

Figure 02: Logistic Regression metric over epoch

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The logistic regression classifier used on the features obtained with the MobileNetV3 showed outstanding results regarding the brain tumor detection in 10 epochs. All of the metrics (Accuracy, Precision, Recall, and F1-Score) were above 0.955 after epoch 10 and the Accuracy was 0.950, which proves the high predictive reliability. It is clinically desirable since it minimizes false diagnoses of the tumors but needs to be monitored because of missed diagnoses. The model stabilized at epoch 6 and had no indicators of overfitting indicating that MobileNetV3 is indeed an effective model to use in transfer learning in this medical imaging task. The results demonstrate the robustness and applicability of the model supporting its future validation on larger and multi-source datasets.

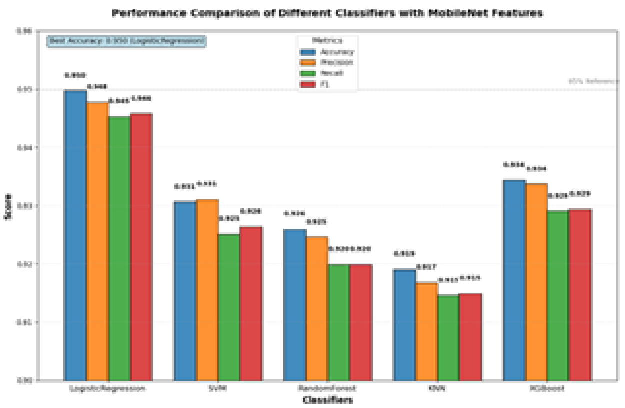

Figure 03: Performance metric comparison on Mobilenet features

According to the above figure 3 of comparative performance analysis LR obtained the best results with the use of MobileNet features which gave the highest accuracy of 95.02 and a high precision of 94.78, recall (94.53), and F1-score (94.58) and outperformed XGBoost (93.44%), SVM (93.06%), RF (92.60), and KNN (91.91) in all evaluation metrics. This generalized high accuracy demonstrate the MobileNet derived features produce a representation space and separated linearly eliminating the need to use more complex nonlinear classifiers and making LR the most efficient and effective solution to apply in cases of using MobileNet feature extraction.

This heatmap figure 04 is a comparison of the performance of 5 classifiers based on MobileNet features but the metrics are truncated to three decimal places to make the figures clear. LR proves to be a better representation of all evaluation dimensions with the highest scores in the dimensions of accuracy (0.950), precision (0.948), recall (0.945) and F1-score (0.946).

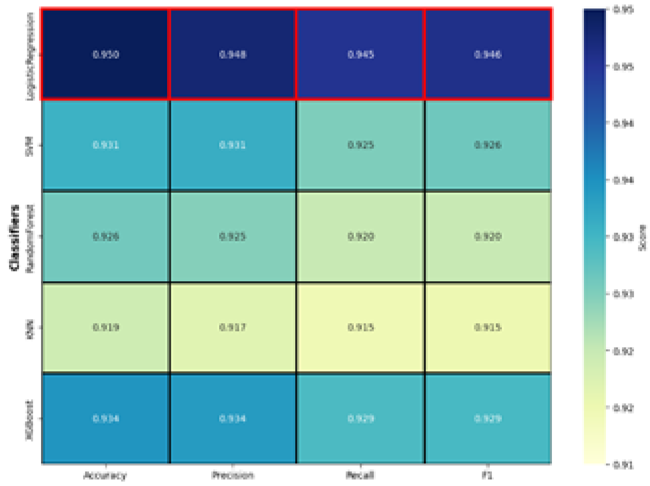

Figure 04: Heatmap for evaluation metrics

XGBoost comes second in terms of performance and KNN has been recording lowest metrics. The light to dark colour gradient is also visually used to support the hierarchy of performance by indicating that traditional LR performs better than ensemble algorithms in combination with MobileNet extracted features indicating that the features produce an image that is almost linearly separable in its features.

V. CONCLUSION

This research validates a hybrid AI framework where MobileNetV3-extracted features combined with Logistic Regression achieved optimal brain tumor classification (95.02% accuracy), surpassing more complex ensemble methods. The results suggest that deep features from MobileNet create a representation space amenable to linear separation, rendering sophisticated nonlinear classifiers unnecessary. This synergy offers a computationally efficient, highly accurate diagnostic aid that can standardize assessments and reduce diagnostic delays. Future work will focus on validating the model across larger, multi-source datasets and integrating it into clinical workflows for real-time augmentation of radiologist expertise.

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