An Integrated CNN-RNN-SVM Framework for Classification of MRI Brain Tumor Images

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***Abstract*—The early identification and categorization of brain tumor through MRI scans are pivotal for effective medical intervention. The present article encompasses a novel integrated framework that combines traditional machine learning and deep learning methods to categorize images of brain tumors. Utilizing the VGG-19 model pre-trained on ImageNet, we extract high-level features from MRI images, which are further processed by a Long Short-Term Memory (LSTM) framework to extract spatial and temporal dependencies within the data. To manage the high-dimensional feature space effectively, we employ Principal Component Analysis (PCA) for dimensionality reduction, followed by a Support Vector Machine (SVM) for the final classification task. We utilized a variety of data augmentation approach to enhance the capability of the architecture to generalize. Additionally, we fine-tuned the training parameters by employing the Adam optimizer along with early stopping and learning rate decay strategies. The model demonstrated exceptional precision, recall, and F1-score metrics, with an accuracy of 97.86%. This study not only validates the effectiveness of integrating CNNs, RNNs, and SVMs but also opens avenues for future research in medical image analysis using hybrid deep learning frameworks. Experimental outcomes demonstrate that the proposed model significantly improves the accuracy of brain tumor classification compared to previous methods, offering a promising tool for aiding radiologists in the rapid and accurate diagnosis of brain tumors.**

***Index Terms*—Brain tumor classification, Deep learning, Data augmentation, medical diagnostics.**

I. Introduction

Brain tumors affect the whole central nervous system of the human body and as a result generate serious healthcare concerns. As per the World Health Organization (WHO), the location of a tumor, its histological characteristics and behaviour decide the types of brain tumors. They are graded on a scale of from 0 to 2 depending on the magnitude as well as the effect on performance ranging from I to IV; the IV being the most severe. tumors which, often, is considered to be the significant factor that reduces patients' survival rate. Brain tumors account for eighty five percent to ninety percent of all major central nervous system (CNS) cancers. Growing at this rate and considering the trends that have been exhibited, in 2023 it is far anticipated that there could be 24,810 fresh cases of number one malignant brain and spinal cord tumors in the organisms of the adult population in United States with a record of 14, 280 incidences. In a male, we expect 10,095 and in women, 10,530 [1]. The lifetime danger risk of developing this form of tumor is less than 1% . Effective to properly manage brain tumors it is imperative that one has to undergo a combined treatment. The diagnosis of the tumor method charges according to the nature of the tumor and its size and location. The patient's mean fitness is crucial for precise diagnosis and prime treatment plans. Classifying brain tumours through MRI is an essential component of this business as it allows for identifying the customers that are more likely to buy the product. MRI provides more detailed pictures of the soft tissue of the brain. Tissues make it an essential instrument in diagnostics, disease identification, and assessment of brain tumors. The task of brain tumor perspective is to introduce the prevalence and clinical characteristics of brain tumors. Classification through MRI entails coming up with a simple or complex distinction based on the outcomes of MRI results. Several sorts of tumors, including gliomas, meningiomas, and schwannomas, differ in many aspects concerning malignancy and treatment strategies. Each tumor type poses several specific issues because of its rate of growth and geographical setting, as well as its effect on other nearby structures of the nervous system. Consequently, It is notably important to assign the patients into the correct groups as possible as it can be to achieve the best results. The traditional classification of the tumour is usually based on the medical personnel's or radiologists' previous experience, acting under visual perception when reading MRI scans. However, this process is not always very formal and differs from the observer's experience. Therefore, improving the reliability and the objectiveness of MRI in tumour. Artificial intelligence (AI), and particularly machine learning (ML) and deep learning (DL) techniques, have dramatically changed the area of medical imaging. Analysis by offering elegant functions in a computer.Vision jobs include image categorization, segmentation, and more feature extraction [2]–[5]. This makes it significant to note that the two classes of algorithms are ML and DL especially compared to the last extensive semantic definition in the description of highly detailed imaging data from multiple modalities as MRI and computed tomography (CT) scans. Medical pictures, helping physicians to be on time neoplasms of the brain: methods of identification, methods that lead to accurate diagnosis, and methods that will allow for proper planning [6], [7]. Stages of tumors, allow for great training and assessment of the model. The methodology comprises a preparatory stage for the process of raw data normalization. The study is organized into separate sections: Section 2 describes the related work of the present area. Section 3 provides a more extensive clarification of the expected approach, which incorporates the architectural design of the VGG19-LSTM-SVM model. The results of the proposed model are presented in the section 4. Section 5 of the study serves as the conclusion.

II. Related Work

Recent literature in brain tumor classification has increasingly focused on leveraging advanced machine learning architectures to improve diagnostic accuracy. Ejaz et al. [8] employed deep convolutional neural networks (CNNs) to detect and categorize brain cancers in MRI data. In addition, they employed conditional random fields (CRFs) to enhance segmentation, standardize intensity as a preprocessing measure, and incorporate it into the dataset. Chetana et al. [9] presented transfer learning-based convolutional neural networks (CNNs), more specifically the VGG-16, ResNet-50, and Inception-v3 models that have already been trained, to automatically predict brain tumor cells from MRI images. Their primary goal is to assess the efficacy of the models by evaluating the accuracy of their predictions. Javeria et al. [10] introduced a methodology that integrates segmentation techniques with feature selection and support vector machine (SVM) classification. The methodology was used to a brain MRI dataset. Hanan et al. [11] trained a Convolutional Neural Network (CNN) architecture on MRI images in to automate the classification of brain tumors. Anil et al. utilizes machine learning techniques, including preprocessing, segmentation using Chan-Vese (C-V) technique, feature extraction with gray level co-occurrence matrix (GLCM), and classification using support vector machine (SVM) validated with K-Nearest-Neighbour (KNN), to accurately diagnose brain tumors from MRI images in [12]. Chenjie et al. [13] proposed expanding brain MRI datasets with a paired generative adversarial network (GAN) framework in order to address the issue of insufficient data and inadequate modalities. Javaria et al. proposed an approach that combines DWT-based MRI sequences, with PDDF for noise reduction, global thresholding for segmentation, and a CNN model for tumor/non-tumor classification [14]. Rahman et al. suggested a parallel deep convolutional neural network (PDCNN) architecture in for classification applications [15]. Irmak et al. [16] employed three CNN models to multi-classify brain tumors with high accuracy. They optimized the hyperparameters using grid search and compared the models with state-of-the-art CNN framework for brain tumor categorization. Aurna et al. use a two-stage feature ensemble of deep CNNs along with PCA to choose the best features and make the classification more accurate. This allows for accurate and automatic classification of brain tumors across MRI datasets, with an average accuracy of 99.13% [17]. Using an automated method Vankdothu et al. [18] prepare MRI images, better K-means clustering for segmentation, a gray level co-occurrence matrix (GLCM) for feature extraction, and recurrent convolutional neural networks (RCNN) for image classification. Amin et al. [19] used DWT fusion, PDDF noise removal, global thresholding for segmentation, and CNN for brain tumor classification.

Ismael et al. [20], utilize residual networks for classifying brain tumors using an MRI image. Rehman et al. utilize transfer learning with convolutional neural networks (AlexNet, GoogLeNet, and VGGNet) on MRI dataset for brain tumor categorization [21]. Noreen et al. [22] presented a framework for automatic diagnosis that uses deep learning and machine learning, along with improved Inception-v3 and Xception models for finding features and grouping them into various categories. To categorize common types of brain cancers into groups, Polat et al. [23] employed transfer learning using VGG16, VGG19, ResNet50, and DenseNet21 networks that had been trained on MRI data. Compared to several deep neural network designs, Veeramuthu et al. [24] proposed a combined feature and image-based classifier (CFIC) that performs better in classifying images of brain tumors. Deep learning algorithms are used in a novel technique by Mehrotra et al. to categorize brain tumors into two types: benign and malignant. Based on T1-weighted MRI images, it has an accuracy of 99.04%, making it highly accurate [25]. To obtain high accuracy and much shorter execution times for brain tumor analysis, Kesav et al. in [26] developed a unique architecture that combined an RCNN for tumor identification with a two-channel CNN for classification. Raja et al. employed a hybrid deep autoencoder with Bayesian clustering using fuzzy logic to classify brain tumor [27].

III. PROPOSED METHODOLOGY

The methodology employed in the described model seamlessly integrates deep learning with classical machine learning techniques, specifically tailored for categorization of MRI brain tumor images. It utilizes a VGG19 neural network, pretrained on the ImageNet dataset, modified to serve primarily as a feature extractor. The upper layers are altered to accommodate an LSTM in the VGG19 model, and the blocks that are typically involved in Max Pooling are also slightly changed. LSTM is applied to capture temporal dependencies and complex relationships in the sequence of image features. This is highly beneficial for augmenting the model's interpretative ability. concerning the geographical stratification that exists in the data set. To maintain the architecture of the pre-trained features, all layers of the VGG19 model are frozen, and batch normalization has been used following the LSTM to make sure that the training is continuing properly, efficiently and stable. The model uses Adam, which was chosen after evaluating several optimizers. Optimizer is widely known for its capabilities in performing the procedural functions of administration of packaged applications and/or large transactional databases for and on behalf of organizations satisfactorily. less gradient and noisy data set. It employs categorical crossentropy as a loss function which makes it appropriate for the specific multi-class classification challenge at hand. A dynamic in addition, a learning rate scheduler is also introduced to further adjust the out during the train epochs because new information is continuously accumulating throughout the learning process. it reduces the number of free trials the client gets or the rate according to the predefined decay function. In terms of as for the data handling, the methodology includes pre-processing and loading of the data. Defining directories containing images and sorting them after the preprocessing, categorising them, and resizing them according to the models. input specifications. Robust data augmentation strategies, such as random flipping, changes in the level of brightness and contrast, as well as changes to its saturation and or hue, are used to enhance the variety in the dataset for deployment applications. This is because, through diversification, the model adjusts to different variations and, therefore, generalizes in the best way possible to new and novel images by imitating an assortment of photographic conditions. Here it is necessary to mention that the training process is based on using the augmented images. The process of using strategic calls to increase the effectiveness of the training process outcomes: Model Checkpoint, which helps in saving the best iteration of the model depending on the validation accuracy; we have EarlyStopping to reduce learning rate for those epochs where further optimisation is not observed and a learning rate scheduler for changing the rates during training epochs. The model's performance is being validated during training by means of assessments that are conducted on an on-going basis. a distinct test set. After the training is done, the model is applied to extract various and complex vectors from the training and testing datasets. They are then passed through to decrease the dimensionality of the images; Principal Component Analysis (PCA) is used. Reduction of dimensionality improves the speed of computation and possibly improves the performance of classification by reducing noise interference. An SVM classifier, highly recognized for its effectiveness in high-dimensional spaces and its ability to use the kernel trick to handle non-linear decision boundaries, is subsequently trained on these PCA-reduced features. The classifier's effectiveness is thoroughly evaluated using the test dataset, culminating in a comprehensive classification report and a confusion matrix. These tools provide detailed insights into the classifier's performance across various classes, highlighting strengths and pinpointing areas for improvement.

In Figure 1 proposed model represent deep learning feature extraction capabilities with traditional machine learning classification techniques, exemplifies a sophisticated and effective strategy for addressing complex image classification tasks, particularly within the realm of medical imaging analysis.

A. Dataset

The dataset comprises 7023 MRI images which are obtained from Figshare, SARTAJ, and Br35H [28]. Some sample images are shown in In Figure 2. These images have been categorized into four groups: glioma, meningioma, no tumor, and pituitary. This varied assortment is crucial for precise analysis of brain tumors using sophisticated image processing and deep learning approaches. Medical image analysis researchers greatly benefit from these datasets since they allow for the creation and evaluation of machine learning algorithms for automated tumor detection and categorization. The addition of a ”no tumor” category from the Br35H dataset offers crucial reference images of healthy brain structures, hence improving the accuracy of tumor detection algorithms. Utilizing these datasets and contemporary technologies enhances diagnostic capabilities, resulting in enhanced patient outcomes and contributing to the wider domain of medical imaging research.

B. Data Augmentation

The data augmentation method has been applied to the training dataset to increase the efficiency of the proposed models. The data augmentation helps overcome the proposed model's generalisation issue, as shown in Figure 3. It helps to find different data generated by original data in different real-world scenarios. Random horizontal and vertical flips have been applied to the images. These flips enhance the model's capacity to classify tumors by making it invariant to the direction of features, regardless of their orientation within the scan. The random modifications have been utilized for brightness, contrast, saturation, and hue of the images to introduce diversity in their visual characteristics. The model encounters many different visual variations during training, which enhances its ability to handle different real-world situations and improves its performance on unfamiliar data. We have incorporated random translations in width and height and colour and orientation alterations.

IV. Experiment Result

All The study leveraged a publicly available dataset containing 7,023 MRI images from sources including Figshare, SARTAJ, and Br35H [26]. These images were classified into four categories: glioma, meningioma, pituitary tumors, and non-tumorous images. There are 1113 images in the test dataset and 5712 images in the training dataset. We employed a structured approach for training and testing brain tumor categorization model, aiming to enhance its performance, validate its applicability across different settings, and provide

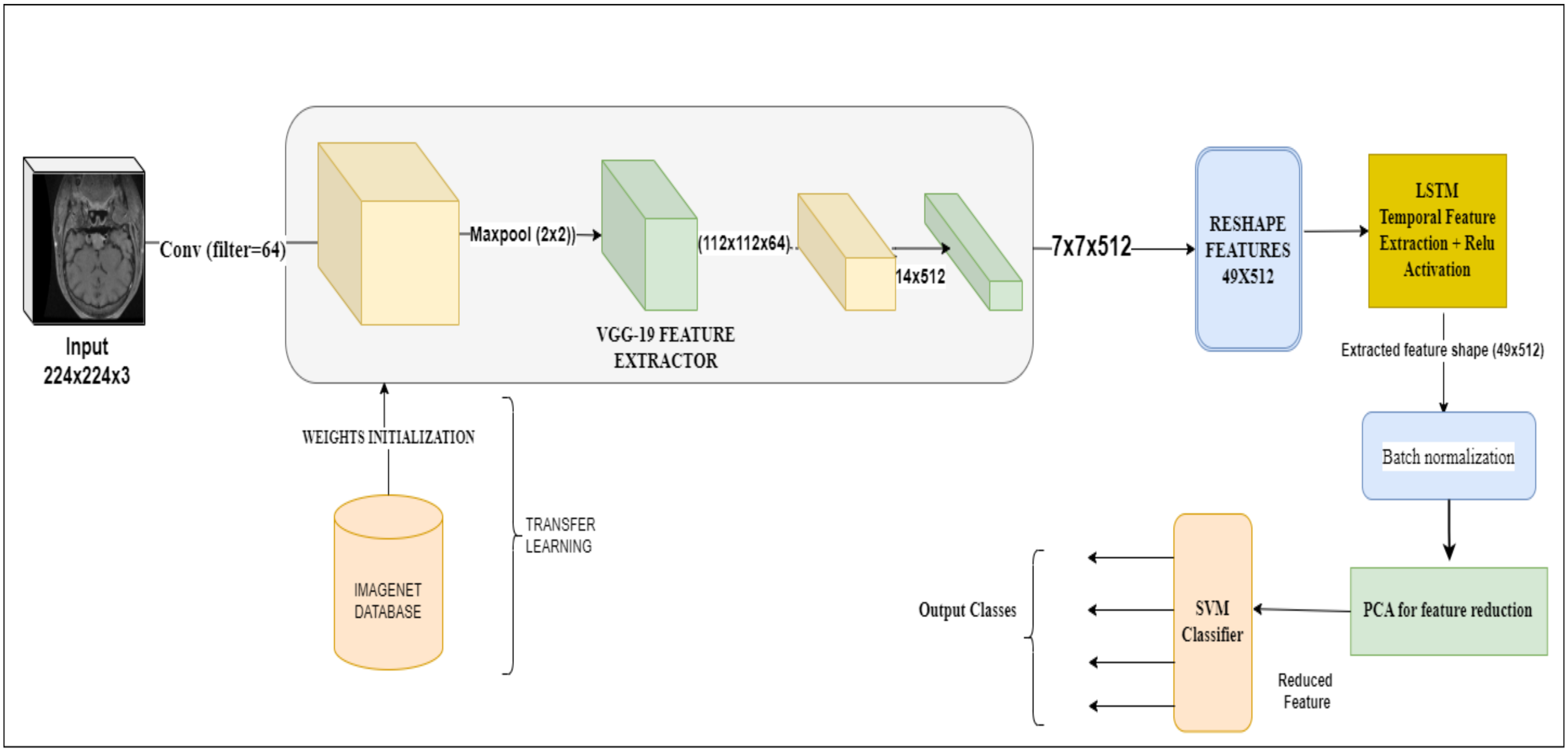

Fig. 1. Proposed model for brain tumor classification.

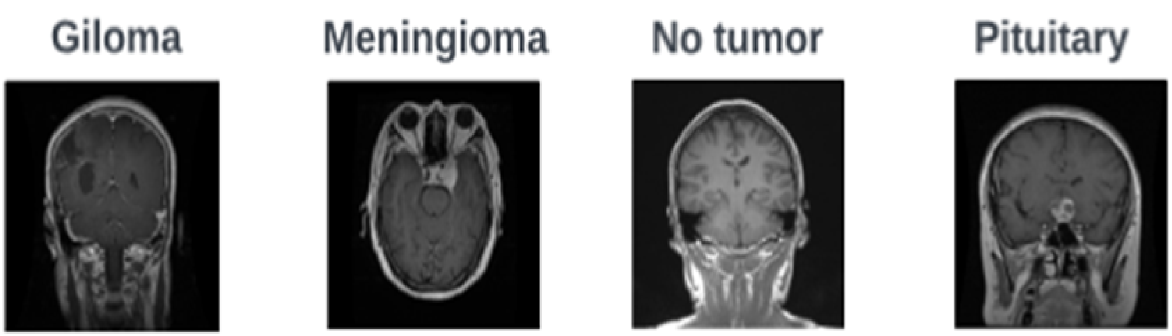

Fig. 2. Sample images of brain MRI.

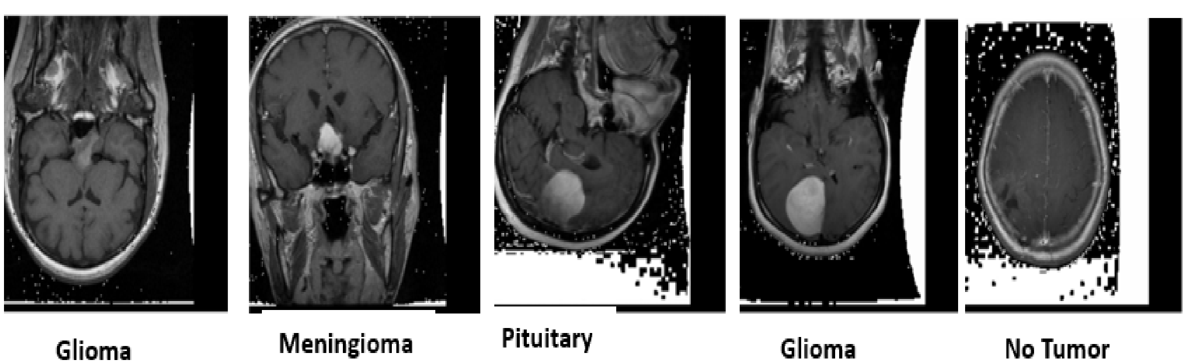

Fig. 3. Augmented image of MRI dataset.

TABLE I
APPLIED PARAMETER IN PROPOSED MODEL.

Variable	Value
Dimensions of image	224 x 224
Channels	3
Epochs	50
Convolution layer activation	ReLU
Compiler optimizer	Adam
Decay_rate	0.95
Dropout	50%
Compiler loss	Categorical cross-entropy
Learning rate	1.00E-03

TABLE II
CLASSIFICATIN OUTCOME OF PROPOSED MODEL.

No. of classes	Precision	Recall	F1-Score	Accuracy
Glioma	98.59	93.33	95.89	97.86
Meningioma	93.48	98.37	95.86	
No Tumor	1	1	1	
Pituitary	99	99	99	

an in-depth analysis of the classification outcomes. Simulations were conducted on an AMD Ryzen 97950X 16-core processor equipped with 64 GB of RAM and an NVIDIA GeForce RTX 4070 GPU. Experimental test including python programming environment, to efficiently develop and train the models. Our data handling process involved loading and preprocessing images from specified directories, categorizing them, and resizing them to meet the model's input specifications. Data augmentation methods were applied to broaden the dataset's diversity, thereby improving the model's capability to generalize effectively to novel, unseen images through the simulation of various photographic scenarios. The model begins with an input layer designed to process images of 224x224 pixels with three color channels (RGB). Utilizing the VGG19 network, pretrained on the ImageNet dataset, as a base model, it acts as a feature extractor where the upper layers are omitted to make room for subsequent LSTM layers. To adapt to the pretrained model's constraints, all layers of VGG19 are frozen, ensuring that their pretrained weights remain unchanged during training. The output from VGG19 is reshaped to match the input requirements of the LSTM layer, transitioning from a 3D output to a 2D sequence. An LSTM layer with 512 units processes these sequences, capturing temporal and contextual dependencies within the data. This is followed by a batch normalization layer, which normalizes the activations from the LSTM to improve training stability and speed. The Adam optimizer is used to assemble the model with a predetermined initial learning rate of 1e-3. Categorical crossentropy serves as the loss function, appropriate for multi-class classification scenarios. We employed the TensorFlow and Keras frameworks to implement deep learning components, and incorporated and assessed the SVM classifier using scikit-learn. This comprehensive toolkit facilitated a strong and smooth workflow for the development, training, evaluation, and analysis of models. Table 1 show the employed parameter in proposed framework.

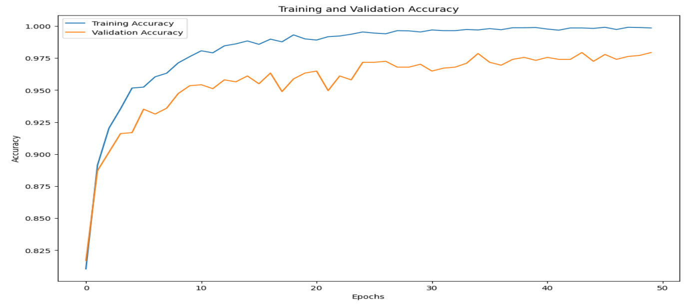

Fig. 4. Accuracy graph of training and validation.

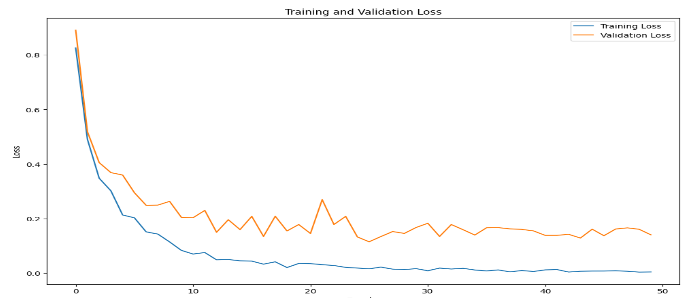

Fig. 5. Loss graph of training and validation.

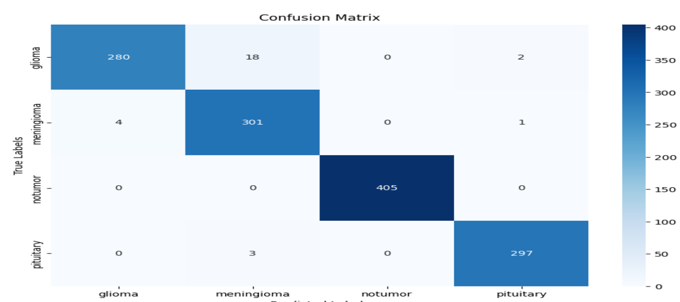

Fig. 6. Confusion matrix of brain tumor classes.

TABLE III
COMPARISON OF MODEL PERFORMANCE WITH EXISTING METHOD

Authors	Model Used	Accuracy
Chenjie [13]	Pairwise GAN	88.82%
Irmak [16]	CNN	92.66%
Vankdothu [18]	RCNN	95.17%
Noreen [22]	Inception-v3 and fine-tuned Xception	94.34%
Shaik [29]	MANet	94.91%
Bodapati [30]	InceptionResNetV2+ Xception	93.69%
Proposed Model	**VGG19+LSTM+SVM**	**97.86%**

In Figure 4 and Figure 5 visual representations of training and validation metrics are plotted to visually track the advancement of model accuracy and loss over time, offering a clear visual representation of the learning trajectory and the efficacy of the applied methodologies. Table 2 displayed important performance measures, including accuracy, precision, recall, and F1-score of proposed model. The confusion matrix in Figure 6 visually represents the model's categorization performance for different tumor classifications. Analyzing the diagonal cells of the matrix, we observe the number of correct predictions the model has made for each class. Specifically, the model accurately predicted glioma in 280 cases, meningioma in 301 cases, no tumor in 405 cases, and pituitary tumors in 297 cases. These diagonal entries highlight the model's strength in correctly identifying each category, indicating a high level of accuracy.

We have included Table 3 to evaluate and benchmark our model's performance against existing models. This comparison represents our model's practical application potential as well as its strength and efficacy in accurately categorizing images of brain tumors. The ensembaling of VGG19 and LSTM gives good result due to its robust feature extraction properties and sequential processing of LSTM.

V. CONCLUSION

The proposed work is focused on the categorization of brain tumor based on combination of convolution neural network and traditional machine learning methods. The proposed model consists of transfer learning model VGG19 for feature extraction and LSTM for sequential feature learning. The classification has been performed with the help of SVM classifier. The data augmentation has been used to increase the usefulness of the proposed model. The overall efficiency of the proposed model is 97.86%. The model has been validated on the datasets Figshare, SARTAJ and Br35H. The results of the proposed model outperform the existing models.

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