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Brain Tumor Classification using Fine-Tuning based Deep Transfer Learning and Support Vector Machine

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Abstract: One of the leading reasons globally of cancer-related deaths is brain tumors. The classification of brain tumors is a challenging research issue. Concerning intensity, size, and shape, brain tumors show high variations. Tumors can display similar appearances from different pathological types. To classify and diagnose brain tumors, there are several imaging techniques utilized. Fortunately, because of its prior quality of image, and also the reality of depending on no ionizing radiation, Magnetic Resonance Imaging (MRI) is generally used. With recent developments in deep learning, artificial intelligence (AI) methods can assist radiologists in understanding medical images rapidly. This paper proposes a brain tumor classification method that employs a deep transfer learning method with a new fine-tuning strategy and a Support Vector Machine (SVM) as a classifier. First, preprocessing is applied to MRI images. Second, the data augmentation technique is applied with resampling to increase the dataset size. Then, the extracted features are from a pre-trained custom Convolutional Neural Network (CNN) model and the ResNet-50 method by using deep Transfer Learning (TL). Generally, after the convolution layers, features are flattened and directly given to SVM for classification. On the other hand, this work applied a new fine-tuning of the parameters for transfer learning. In particular, dense layers with dropout and Rectified Linear Units (ReLU) are applied after flattening. Then, the output of the final dense layer is given to SVM for classification. The efficiency of the proposed transfer learning-based classification approach using different settings is tested on the Figshare dataset which includes the three sorts of MRI brain tumors; meningioma, glioma, and pituitary. Results show that the proposed deep transfer learning approach is adequate; transfer learning using the proposed CNN architecture with fine-tuning and SVM classifier achieves 99.35% accuracy, whereas transfer learning that use ResNet-50 with fine-tuning of parameters yields a classification accuracy of 99.61%. The results of the proposed approach are very promising compared to state-of-the-art on the Figshare dataset.

Keywords: Brain Tumor Classification, CNN, ResNet-50, Transfer Learning, SVM, Figshare Dataset

1. INTRODUCTION

The brain in the human body is the management center. It is accountable to function all processes through a huge group of neurons and many connections. One of the most devastating diseases is brain tumors, leading to a very short life hope at their highest level. Therefore, early diagnosis of tumors is vital that relies on the doctor's experience and knowledge. As a result, ill persons have an opportunity to resume their survival and life [1]. Various kinds of brain tumors could either be benign or malignant.

The benign tumor is not a progressive and cancerous form, it originates inside the brain and also gradually develops. Such kind of tumor will not be dispersed in the human body, and it is considered to be less aggressive. A malignant tumor is a cancerous and progressive form. It breaks away rapidly through unknown borders, invades other normal tissues, and spreads to all areas of the body. If the tumor is placed in the center of the brain, it is defined as a primary malignant tumor. Once it emerges in the other parts of the body, it extends to the brain and it is also recognized as a secondary malignant tumor [2].

Brain tumors could be categorized into two classes, including primary and secondary. The primary accounts for approximately 70% of all tumors of the brain, while the remaining 30% are secondary tumors. This category is defined by the origin of the tumor; just as primary tumors are considered tumors that first originate in the brain. On the other hand, within malignant, its first tumor called primary appears in some other part of the body and then, it is changed to its secondary tumor that is moved to the brain, and both of them are malignant.

In 2015 , in the United States of America, approximately 23,000 patients had been diagnosed with brain tumors. A

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brain tumor is estimated as the main reason of cancer-related sickness, mortality, and morbidity globally. By 2017 statistics on cancer, and brain tumors were found in both children and adults [3].

The most significant types of brain tumors are meningioma, glioma, and pituitary: Meningioma is the most common type of benign tumor that instigates the soft membranes that cover the spinal cord and brain. Glioma tumors are several tumors that develop inside the brain. High-grade glioma is the most dangerous brain tumor, with at least a survival of approximately two years. In pituitary tumors, brain cells abnormally become large. In this sort of tumor, the gland of the brain grows as well. These tumors are similar in shape, inherent, and nature. The spreads in any place in the brain [4].

The significant variation among the three kinds of tumors is meningioma usually is benign, while gliomas are often malignant. Pituitary tumors, even if they would be benign, they able to lead to many medical side effects, dissimilar to slow-growing meningioma tumors. Since as the details described above, the accurate distinction among these three kinds of tumors represents a very significant phase in the clinical diagnosis process and later impressive evaluation of patients [5].

Brain tumor image testing is conducted by using x-rays and powerful magnets, or radioactive substances, to generate brain images. Brain tumors are usually diagnosed using several kinds of scans including Magnetic Resonance Imaging (MRI), Computer Tomography (CT), Emission Tomography Myelogram (ETM), Positron, and Angiogram are among the kinds of scans that are used mostly to diagnose brain diseases. These images are so effective that they can provide primary information about the tumor's location and the existence of brain tumor classifications even among subtypes as research challenge problems. To identify, segment, and classify brain tumors, various imaging methods can be used. However, the most prominent prevalent technique is non-invasive MRI. The success of MRI comes from the ability to use no ionizing radiation within the X-Ray and scan, also its better resolution of thin tissue. In addition, the capability to obtain various images apply different image parameters or use contrast-enhanced factors [6].

For the segmentation, detection, and classification of brain tumors, several methods were suggested. In the field of medical imaging, machine learning has appeared widely as a subclass of AI. Machine learning is the analysis of the statistical, algorithm, and mathematical equations that can be used to perform a particular task instead of focusing on patterns without using straightforward instructions. K-Nearest Neighbors (KNN), Artificial Neural Network (ANN), and Support Vector Machine (SVM) are types of supervised algorithms. Unsupervised learning, on the other hand, is depending only on input variables in clustering such as Fuzzy C-Means (FCM) or Fuzzy K-Means (FKM) and Self Organization Map (SOM) [2].

Deep Learning is commonly applied for the analysis of brain images in many practices, including normal and abnormal brain tumor segmentation [7], detection [8], and classification [9] (non-enhancing tumor zone, enhancing and edema) stroke lesion segmentation, Parkinson's, Alzheimer's, and brain tumor diagnosis, etc. Deep learning is a type of artificial neural network that contains multiple hidden layers in which multiple processing layers are used to gradually extract higher-level of data elements that help to overcome several challenges that occur in traditional machine learning methods [10]. Deep learning started to be very popular for medical applications such as medical imaging to recognize damaged sections of any object, and it is also helpful to categorize the images and prediction techniques of the object [11]

Computer-Aided Diagnosis (CAD) programs have assisted neurologists. Additionally, neurological CAD applications support tumor segmentation, grading, detection, and classification [12]. In this context, deep learning, especially, Convolutional Neural networks (CNN) is consumed for both feature extraction and classification as a combined unit. There is a significant interest in using CNN to develop CAD systems. The CAD systems which have used CNN have been extremely successful and obtained remarkable outcomes. CNN works well, but when the data size is small, they begin to overfit. To amend this error of overfitting, transfer learning concepts with pre-trained deep CNN models and data augmentation are developed [13]. Transfer Learning (TL) is another concept of deep learning models to deal with performance issues. These tasks gained from the prior models have applied this information to another domain. Thus, if the dataset is small, this technique is very important. When the data number is relatively small, after many epochs, the model begins to over-fit. If the dataset is huge, the learned features could be applied to categorize various sections that are not available in the utilized basic dataset. Another benefit of TL is that there is no need for high computational power [14].

Even though many advances have been made in brain tumor classification, the categorization of brain tumors according to their sub-type is still a challenging task. Brain tumors of the identical category may have differences based on various patient-specific agents in structure, size, and shape. Tumors from different categories, on the other hand, could display similarities. This act makes the issue more complex. In contrast, limited studies have been published to categorize brain tumors into various pathological sorts.

In this paper, the classification of brain tumors into three tumor types is performed using a novel deep transfer learning method on the Figshare dataset [15]. Although, in the literature, there are deep transfer learning-based methods on Figshare dataset, none of the methods apply deep transfer learning using ResNet-50, a custom CNN and SVM together for classification of brain tumors on Figshare dataset with a fine-tuning strategy. In particular, a custom CNN architecture and ResNet-50 with transfer learning is used, as well as, a new fine-tuning strategy is applied to extract transfer learning features and a SVM classifier is utilized for the classification. Generally, after the convolution layers, features from the pre-trained network are flattened and directly given to SVM for classification. On the other hand, this work applies a new fine-tuning of the parameters for transfer learning. In particular, dense layers with dropout and Rectified Linear Units (ReLU) are applied after flattening. Then, the output of the final dense layer is given to a multi-class SVM for classification into three categories. Results show the proposed method is very promising and provides one of the best results on the Figshare dataset. In particular, the proposed CNN architecture with fine-tuning strategy and SVM classifier achieves 99.35% accuracy. Transfer learning using ResNet-50 with fine-tuning of parameters yields also high classification accuracy of 99.61%. The proposed transfer learning-based solutions can also be applied to other medical image domains such as breast, lung, and liver tumor classification.

2. RELATED WORK

For the classification of brain tumors, diagnosis, and segmentation, various methods and approaches have been suggested; including computer vision methods, image processing techniques, machine learning, and deep learning algorithms [7]. Especially, existing studies indicate that deep learning techniques can provide state of the art performances for detection and classification of brain tumors using MRIs. As a result, it is possible to provide a quick diagnosis of the tumor type, size, and location by doctors, which can significantly increase the life expectancy of the patient. This is the motivation of our work. In the existing related works, there is room for improvement for classification accuracy. For this purpose, in our work, a custom CNN architecture and ResNet-50 are used with transfer learning and a new fine-tuning strategy for extracting transfer learning features. Then, SVM classifier is employed to categorize the brain tumor type on the Figshare dataset [15]. Below, methods that use Figshare dataset are summarized.

The first method on the Figshare dataset for brain tumor classification is presented in [16]. Three methods for extraction of features are used, intensity histogram, Bag of Words (BoW), and Gray Level Co-occurrence Matrix (GLCM). The aforementioned researchers compared the classifiers by intensifying tests they reached good results in diagnosing the brain tumor regions. The best result is obtained by an association of BoW features and an SVM classifier. Five-fold cross-validation was followed by experiment assessment and overall accuracy of 91.28% is obtained.

[17] presents an machine learning-based approach to classifying brain tumors in MRI images that incorporates neural network algorithms and statistical features. They employ feature extraction of brain MRI by using a combination of the Two-Dimensional Gabor filter technique and the Two-Dimensional Discrete Wavelet Transform (DWT) algorithm. The authors apply a multilayer perceptual neural network (trained back-propagation neural network) for classification. A huge dataset including 3,064 images of T1-weighted MRI of the three sorts of brain tumors such as meningioma, glioma, and pituitary tumors are used. They achieve an accuracy of 91.9% on the Figshare dataset.

Since machine learning and conventional computer vision methods require hand-crafted features, recent works on brain tumor classification are based on deep learning. Especially, CNNs are utilized for the diagnosis of brain cancer classification. CNN requires no previous information on feature types, but these features are automatically learned by CNN. Also, CNNs could be trained end-to-end and it does not need the segmentation of tumors in MRIs [9].

One of the early CNN-based solutions on the Figshare dataset is proposed by [18]. They introduce a Capsule network (CapsNet) model for the classification of brain tumors based on four objectives that consist of incorporating and adopting a Capsule Network, over-fitting analysis, developing a visualization model for production, and also the capability of cabinets. The research obtains an accuracy of 86.56% in the convolution layer by using Capsule Network.

[19] suggests a CNN technique for feature extraction from brain MRI images. There were five learnable layers in the model, and the filters have a size of 3x3 for all layers. The CNN method claimed to obtain a 93.68% accuracy of classification. Applying CNN features with a classifier process from the extreme learning machine (ELM) class, the performance was enhanced. Within this research, recall measures were very high for the class of pituitary tumors, while they have a very low measure in a meningioma class due to the incapability of the classifier to discriminate against this class.

[20] also uses a deep learning method depending on CNN for the classification of three brain tumors such as meningioma, glioma, and pituitary. The CNN architecture consisting of convolution, flattening layer, max pooling, and the fully connected layer from a single hidden layer came after them. The validation and training accuracies are obtained as 84.19% and 98.51%, respectively.

[21] presents a design that is based on a Genetic Algorithm and a Convolutional Neural Network to classify various kinds of glioma grades by employing an MRI images dataset. Genetic Algorithms are used to automatically pick the CNN architecture. In one setting, they briefly discuss the 90.9% accuracy that was achieved for categorizing three grades of gliomas. Meanwhile, the meningioma, glioma, and pituitary tumor classes were classified with an accuracy of 94.2% in another setting.

[12] Utilizes transfer learning using CNN features and SVM. Features are extracted from CNN and classified by a multi-class SVM. For the three various types of brain tumors (meningioma, glioma, and pituitary) the fully automated method is tested on the Figshare. It is suggested that multi-class SVM help have a better performance. The classification result shows that the method achieves an accuracy of 95.82%.

[22] presents a novel system named Global Average Pooling ResNet-34 for brain tumor classification. Their system contains the below features the implementation of the established CNN model for the classification task in the domain of deep learning called ResNet34, to decrease the number of parameters and prevent overfitting. In place of the flattened layer for the classification, they used the global average pooling layer. They connect the feature vectors of various layers so that to be capable to combine the low-level and high-level features of the network to increase the accuracy of categorization. Furthermore, they introduced a loss function that is the amount of the cross-entropy loss and the interval loss. The total loss is added to the punishment for misclassification. In this work, the system obtained a 95.00% classification accuracy.

Authors in [23] offers the use of deep transfer learning for the automated classification of brain tumors. In this work, researchers experimented with various pre-trained networks, such as Alex-Net, VGG-16, and VGG-19. The architecture applying VGG networks obtained a more proper accuracy much up to Alex-Net. They used pre-trained VGG19 for the brain tumors classification of various layers in the network. The block-wise fine-tuning process resulted in an inaccuracy of up to 94.82%.

Regarding brain tumor identification, [24] presents a new CNN method called BrainMRNet. In each image in this model, they used a preprocessing technique with extracted features and data augmentation using the hypercolumn technique in convolutional layers. The BrainMRNet model is more effective in this work compared to the pre-trained Deep CNN methods of AlexNet, GoogleNet, and VGG-16). With the BrainMRNet model in this work, the classification performance achieved was 96.05%.

In the work of [25], authors present an automated approach for brain tumor classification into different types, the image slice samples are moved to a CNN-based Squeeze and Excitation ResNet technique. They used data augmentation to further enhance the operation. The accuracy of 93.83% is achieved in this study.

In [26], authors propose an approach to classify brain tumors using MRI images by taking advantage of transfer learning. They tested different deep transfer models such as ResNet50, DensNet21, VGG16, and VGG19 with different optimization algorithms for brain tumor classification. Multiple optimization algorithms are also utilized (i.e. ADAM, Adadelta, SGD, and RMSprop) used for training and testing on the MRI Figshare dataset and they measured accuracy as their performance metric. Their proposed approach has the highest accuracy of 99.02% with RestNet50 using Adadelta.

Researchers in [27] propose multiclass classification methods for brain tumors by taking advantage of techniques of machine learning and deep learning. They classified MRI brain images using end-to-end models of CNN (i.e. GoogleNet, and ResNet-18). Furthermore, SVM is utilized to extract deep features from CNN models and classify them. The training and testing took place on the Figshare dataset after performing data augmentation on them to increase the number of images in the original dataset to achieve an accuracy of 98% when they used CNN and SVM together.

Although in the literature there are deep transfer learning-based methods on Figshare dataset, none of the methods apply deep transfer learning using ResNet-50 and SVM together for classification of brain tumors on Figshare dataset. In particular, a custom CNN architecture and ResNet-50 are used with transfer learning, as well as, a new fine-tuning strategy is applied to extract transfer learning features. Finally rather than end-to-end classification within the CNN network, a separate classifier, SVM is employed. This is the novelty of the proposed approach. Results show the proposed method is effective and provide very competitive results.

3. Proposed Deep Transfer Learning-based Method using Pre-Trained Models, Fine-Tuning, and SVM

Deep learning using pre-trained models require large datasets to train in order to alleviate overfitting. On top of that, they require a long time to be trained since generally these pre-trained models (such as Resnet-50) contain many deep hidden layers. As a result, generally pre-trained models require huge computational resources to train the network. However, once the training process is completed, testing can be performed in a much faster time. For example, a user interface for doctors or radiologist (i.e. a desktop-based application) can easily be used over the pre-trained network and receive classification results for the given MRI image. This can decrease processing time of the radiologists and assist them, as well as, provided results can help doctors during the diagnosis. This is the motivation of our work.

A. Algorithm

This work aims to improve the accuracy of the classification of brain MRI by applying machine learning, deep learning, and the approach of Transfer Learning (TL). TL is the task of using the knowledge given by a pre-trained framework to learn new systems provided by new data. It is typically simpler and much easier to calibrate a pre-trained system with TL rather than starting from basics. The use of pre-trained deep learning systems gives us the ability to learn new works quickly. Here, two distinctive deep learning models are reviewed: (1) A CNN architecture is developed that is suitable for brain tumor classification from MRI, and (2) a ResNet-50 pre-trained model is applied. In both cases, different than other works, batch normalization is applied to input MRI images, as well as, after feature extraction by the pre-trained network, fine-tuning is applied to extract effective transfer learning features. In particular, as a first step, batch normalization is employed to the input image; this process normalizes the input layer within the learning cycle and also decreases the computational complexity of model training. Then, feature extraction is applied by either a custom CNN model or ResNet-50. Subsequently, a fine-tuning strategy is employed that is consisting of four dense layers with ReLU, and Dropout. Then, the Softmax layer is applied to obtain normalized class probability values. Finally, these features are given to SVM for classification. The proposed strategy involves the following stages: first, preprocessing is applied to MRI images. Second, resampling is applied as a data augmentation technique. Third, extraction of features based on the proposed CNN architecture and ResNet-50 is performed, where input MRI images are passed from a batch normalization as a first step. Then, before giving the features to SVM, features are fine-tuned; 4 dense layers are utilized and the output of the dense layers are used as feature vectors. Finally, the multi-class SVM classification is applied. To estimate the operation of transfer learning with SVM and fine-tuning, the results are benchmarked with the same settings but without using an SVM classifier. In this case, Softmax Layer is utilized for classification. Figure 1 presents the algorithm. Stages are also summarized below:

1) Input the figshare dataset
2) Preprocessing (Resize and Mask)
3) Data Augmentation (Re-sampling)
4) Batch Normalization to images
5) Feature Extraction (either with a custom CNN+TL or ResNet-50+TL)
6) Fine-tuning of TL features using dense layers with ReLU, Dropout
7) Classification either using Softmax Layer or SVM Classifier (two different settings are tested)

B. *Figshare Dataset*

Figshare T1 weighted MRI brain tumor dataset is available on networks publically and to the researchers specifically. This dataset includes 2-D images of three forms of brain tumors Meningioma, Glioma, and Pituitary. And the dataset consists of three plane views of three kinds of brain tumors Axial, Coronal, and Sagittal views as well. The dataset details are statically shown in Table I. It includes 3064 MRIs of 233 patients from all three perspectives and different kinds of tumors. It also includes 708 brain MRIs of the meningioma corresponding to 82 patients, 1426 glioma images belonging to 89 patients, and the left 930 images referring to the pituitary concerning 62 patients. The dimensions of each MRI are 512x512 pixels [15]. Figshare dataset is used for brain tumor type classification tasks. There are other datasets such as BraTS. However, BraTS dataset is especially used for brain tumor detection and classification of the segmented regions based on their grade.

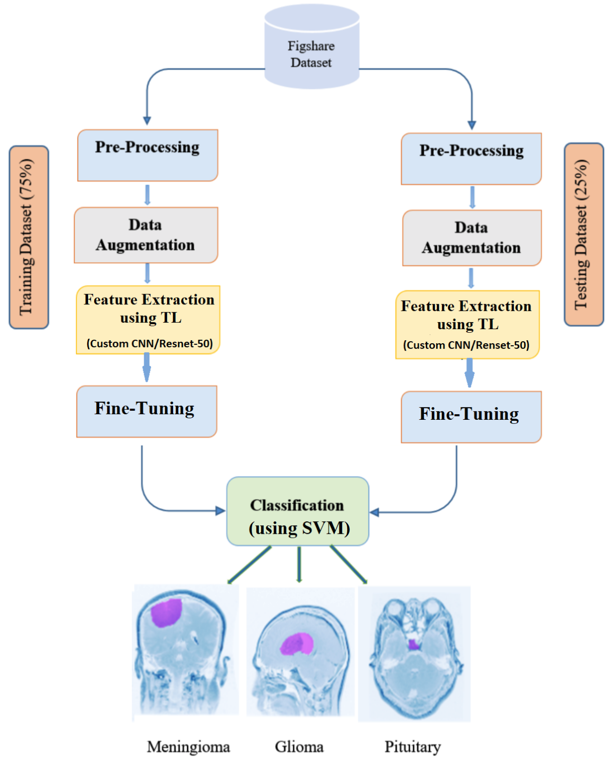

Figure 1. Diagram of the proposed approach using TL, fine-tuning and SVM for brain tumor classification

Since our work focuses on classification of different tumor types, the Figshare dataset is utilized.

C. *Preprocessing*

In this work, pre-processing is the first step. These approaches are very important to improve the input image qualities, and also to provide suitable outcomes for helping diagnosis. Cleaning the MRI images is the first step and activity of medical imaging analysis. It also helps to enrich the input image features, consisting by enlarging the rate of the signal-to-noise in the visual influence of the input samples. Moreover, the preprocessing techniques contain smoothing inner regions, unnecessary noise removal, and edge framing [28]. In this paper, as shown in Figure 2, the pre-processing includes two steps: First, for memory optimization purposes, the input MRI images are resized of the entire set of 233 patients (3064 MRI images total). The size of the MRI images in the Figshare database was 512×512 pixels. But all images are resized by reducing them to 256×256 pixels. The reduction in the image size is important to improve the training performance of the classification task. Without image re-sizing, training takes considerable time with a deep network like ResNet-50. After re-sizing the input image, consequent feature extraction layers can process faster. Thus, computational complexity can be reduced. Second, the mask method is utilized for the detection of tumors in every MRI image. It is used for designating the region, size, and shape of the

Tumor type	No. of patients	No. of images	MRI Views
Meningioma	82	708	209 Axial 268 Coronal 231 Sagittal
Glioma	89	1426	494 Axial 437 Coronal 495 Sagittal
Pituitary	62	930	291 Axial 319 Coronal 320 Sagittal
Total	233	3064	994 Axial 1024 Coronal 1046 Sagittal

TABLE I. Figshare Dataset Details

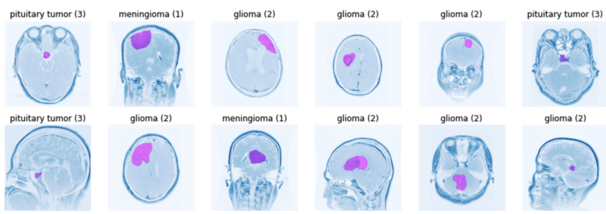

Figure 2. Pre-proceessing MRI images of different tumor types

tumors.

D. Data Augmentation

Data augmentation in computer vision is a significant key reason which has a high influence on the training of deep learning models. Data Augmentation has different techniques like (flipping, scaling, re-sampling, rotation, crops, and shear) [13]. The importance of using these data techniques is to increase the number of the datasets, and also decrease the overfitting problems during the deep learning models within the training process. In this work, data augmentation is applied to generate three samples of each image using the re-sampling technique. Re-sampling technique involves changing resolution of the given MRI image. With more number of input MRI images for training, this augmentation technique helps to improve the accuracy of the proposed approach. The MRI images are re-sampled before entering into the network for the training process. The total number of Figshare MRI datasets contains 3064 images but after data augmentation, the number became 9192 samples, where each image has the same size as the original image in the dataset that includes 256 pixels. In this way, high accuracy can be achieved and avoid overfitting issues. Due to the use of deep learning techniques for classification of brain tumors from MRI images, increasing the sample size with augmentation is important to reduce the risk of overfitting. All the aforementioned process is called re-sampling which is used as one of the data augmentation techniques. It has shown in Figure 3.

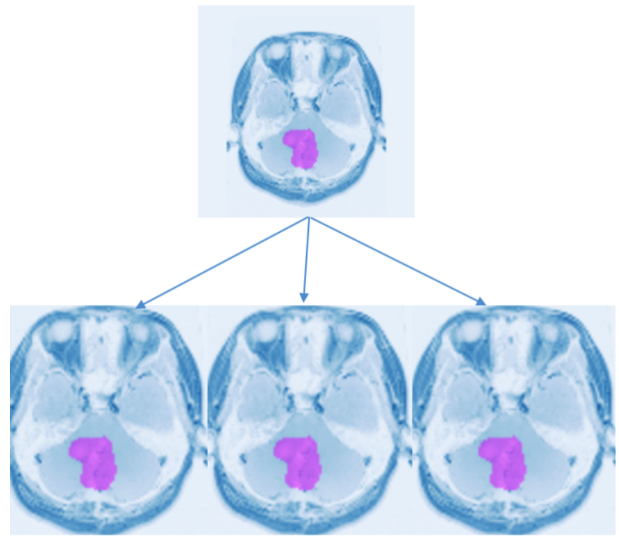

Figure 3. Resampling process

E. Transfer Learning using Fine-Tuning and Freezing Scenario

The goal of Transfer Learning (TL) is to enhance learning through the use of knowledge from the source tasks in the target tasks. Transfer learning is an efficient method for reducing the time needed for training. Rather than commencing the learning process from scratch, prior learning is leveraged by transfer learning [29]. Often, a pre-trained deep learning model is applied which is formerly modeled on a huge benchmark dataset to a new small dataset. In this work, a powerful and innovative approach of deep learning using the transfer learning technique is applied to categorize brain tumors by extracting pivotal characteristics from a standard dataset. This is the main aim of this work. For this purpose, two deep learning models are explored, a CNN model and ResNet-50. By using different architectures and settings, the proposed approach is tested and improved the performance of the Figshare dataset. In this approach, two significant transfer learning scenarios are employed, fine-tuning and freezing together with a SVM classifier.

1) Fine-Tuning

Biases and weights of a pre-trained CNN are implemented, instead of random initialization. Later on, a conventional training procedure on the target dataset is conducted using SVM. The fine-tuning of TL is applied by replacing the last layers of the pre-trained network to enrich the performance and effectiveness of the CNN. In this case, instead of retraining and replacing the whole design of the CNN classifier, ConvNet weights are initialized from the climax of the proposed CNN and ResNet50 pre-trained networks. This idea functions by moving weights from the source dataset (e.g. ImageNet) to the Figshare (target dataset) for the CNN and ResNet-50. The initial layers of the pre-trained networks are kept and replaced with the last layers in this paper (see Figure 4). In particular, 4 dense layers are applied

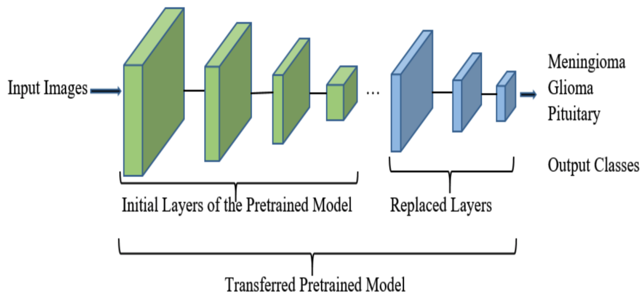

Figure 4. Transfer Learning concept using the pre-trained scenario

with ReLU and softmax. In addition, the final classes of the softmax layer are replaced with three target classes which correspond to the Meningioma, Glioma, and Pituitary classes of brain tumors. For classification, features from the last dense layer are given into SVM. Here, instead of giving the flattened feature vectors from the convolutional layers, the described fine-tuning is applied, which improves the results of the conducted experiments.

2) Freezing scenario

Pre-trained CNN layers are put into consideration as constant feature extraction. The biases and weights of the required convolutional layers in this context are frozen and allow the fully connected (FC) layers to be fine-tuned over the target dataset. In this model, pre-trained network layers are worked and frozen as constant elements. This idea functions by concluding the weights from the ImageNet (source dataset) of the pre-trained model. And the arbitrary vector features can be applied from convolutional layers or from fully connected to train a linear (SVM) classifier on the Figshare (target dataset).

F. Proposed CNN Architecture for Transfer Learning

A typical CNN architecture contains several layers, like convolution, ReLU, pooling, normalization, and FC (dense layer). The phase in which input data via these layers are transformed into output is named forward propagation. To prevent over-fitting, generally, the dropout layer is used after the FC layer. Finally, softmax is used for anticipating the output and eventually the classification layer that generates the expected class.

The proposed CNN model in this work is shown in Figure 5, which is obtained after several experiments on the Figshare dataset. In particular, the best performing CNN model is chosen that gives the highest accuracy on the Figshare dataset. The CNN network takes 256×256 T1 weighted MRI images in the Figshare dataset. In this approach, as a first step, batch normalization is consumed to the input image that is different than many CNN models; this batch normalization process normalizes the input layer within the learning cycle and also decreases the computational complexity of model training. The network contains 4 convolutional layers with a ReLU activation function. Our experiments show that ReLU activation performs better than other activation function. Four max-pooling layers are provided after each ReLU activation function. After convolution layers, a dropout layer is placed to keep away from over-fitting, then a flattened layer is located after the dropout layer. Four dense layers are used to fine-tune the features for classification; the four first dense layers employ the ReLU activation and dropout. Lastly, the Adam optimizer has been applied with categorical cross-entropy as the loss function. Meanwhile, the CNN and the transfer learning are combined by saving the initial layers and fine-tuning (replacing) the last layers of the CNN model. Besides all these, SVM is implemented to diagnose the multi-class classifications of the types of brain tumors such as (meningioma, glioma, and pituitary). The output feature vector of the last dense layer is given to SVM for classification.

Name of Layers	Output Shapes	Number of Parameters
Input Images	(None, 256, 256, 1)	0
Batch normalization	(None, 256, 256, 1)	4
Convolution	(None, 254, 254, 32)	320
Max-pooling	(None, 127, 127, 32)	0
Convolution	(None, 127, 127, 64)	32832
Max-pooling	(None, 63, 63, 64)	0
Convolution	(None, 63, 63, 128)	73856
Max-pooling	(None, 31, 31, 128)	0
Convolution	(None, 31, 31, 128)	65664
Max-pooling	(None, 15, 15, 128)	0
Dropout	(None, 15, 15, 128)	0
Flatten	(None, 28800)	0
Dense	(None, 128)	3686528
Dense	(None, 64)	8256
Dense	(None, 32)	2080
Dense	(None, 3)	99
Total parameters:		3,869,639
Trainable parameters:		3,869,637
Non-trainable parameters:		2

TABLE II. CNN Architecture - Number of Parameters

The total number of parameters of the CNN model are as follows (details are given in Table II): Total number parameters are 3.869.639, trainable parameters are 3.869.637 and non-trainable parameters are 2.

G. Proposed ResNet-50 based Architecture for Transfer Learning

ResNet- 50 is a deep CNN model, introduced by He et al. in Microsoft in 2015. The ResNet-50 took a prior position through ImageNet Large Scale Visual Recognition Challenge (ILSVRC) with a 3.57% error rate [30]. First, the preprocessing phase is carried out to resize and mask of Figshare MRI dataset and match it with the ResNet-50 input size. The ResNet- 50 was originally trained on 1,000 classes of ImageNet datasets [31]. The pre-trained ImageNet weights exclude the final FC layers of ResNet-50 , they are frozen and used for creating a system for the classification issue of brain tumors. The transfer learning approach is applied to the ResNet- 50 model by replacing FC layers with four dense layers with ReLU, dropout, and softmax. Like in CNN with transfer learning, the output

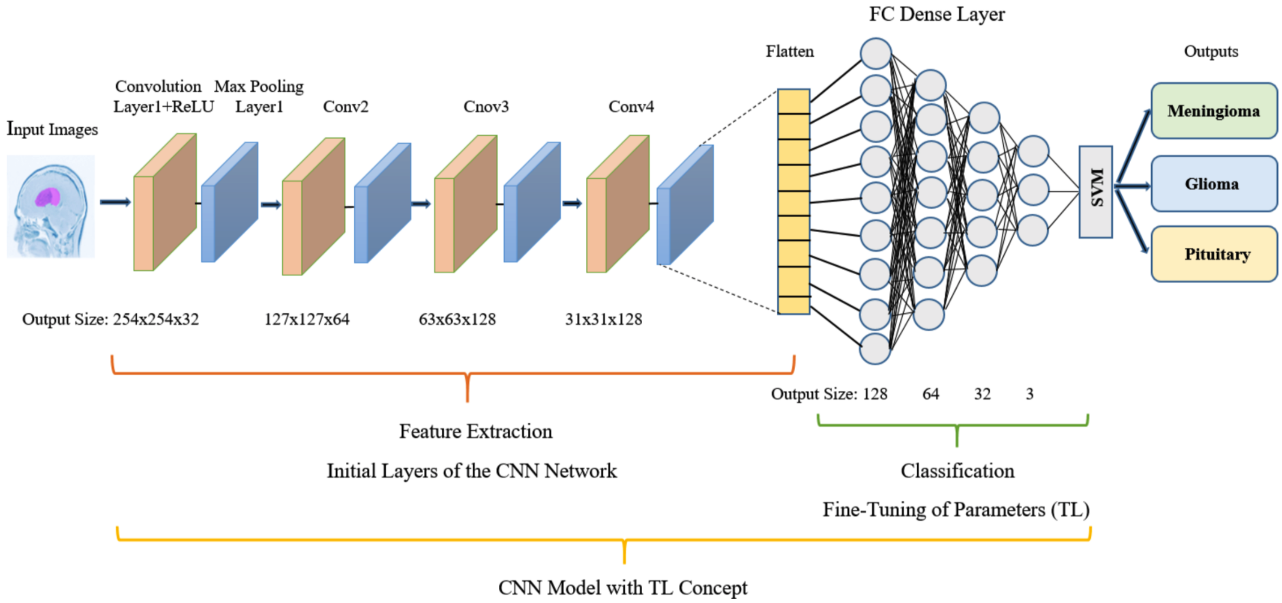

Figure 5. Proposed Custom CNN Architecture with TL, fine-tuning approach and SVM

feature vector of the last dense layer is given to SVM for classification. Different from than proposed CNN + TL approach, batch normalization to the input image in the Resnet- 50 model is not applied. This converted TL-ResNet 50 network has here been trained and fine-tuned rather than 1,000 on a new dataset of 3 classes as well. For extracting deep features, the ResNet- 50 model is trained on the Figshare dataset. Deep features are extracted after the "average-pool" layer before the final FC layers. The TL-ResNet 50 functions as an undetermined feature extractor that authorizes the latest input image to stop and forward propagation in a predefined (avg-pool) layer for achieving deep features. With freezing the pre-trained ImageNet weights, the ability is gained to leverage the discrimination of robustness learning ability of TL-ResNet-50. An optimal deep feature vector of size 2048 has been achieved at the (avg-pool) by hiring the transfer learning model for the classification state.

The mentioned dense layers with ReLU and dropout are applied to fine-tune features, which then are fed to SVM for final classification. ResNet-50 is a residual network with 50 layers. The ResNet- 50 model includes five convolution phases. Conv1 consists of only one convolution layer and has only one convolution block. The remaining layers consist of (Conv2 contains three convolution blocks, Conv3 includes four convolution blocks, Conv4 consists of six convolution blocks, and Conv5 contains three convolution blocks). Each convolution block includes three layers (Conv (1×1), Conv (3×3), and Conv (1×1)). The size of the feature map is changed by down-sampling with the average pooling layer. Separate from these, there is an FC convolution layer for the classification task at the end of the network [32] by saving the initial layers and fine-tuning (replacing) the final layers, good results have been achieved through a combination of SVM as a classifier.

The proposed TL with ResNet- 50 is illustrated in Figure 6 . The total number of parameters of the ResNet-50 model is as follows: Total number parameters are 23.587.523, trainable parameters are 23.534.403 and non-trainable parameters are 53.120. Compared to the CNN model, the total number of parameters is almost 8 times higher.

H. SVM Classifier

In its simple definition SVM is used for binary classification. In this paper, SVM is consumed for multi-class classification and implemented SVM such as a popular supervised machine learning algorithm that is used for the classification of three various types of brain tumors. The rbg kernel SVM is used here. The classification is executed with the creation of decision planes, by which the hyperplane separates the different class features. In particular, to spot the diagnosis of tumor existence from input brain images, the linear SVM-based classification algorithm is operated. Figure 7 shows the topology of SVM for multi-class classification.

4. EVALUATION AND RESULTS

In this part, classification outcomes of CNN along with transfer learning (CNN + TL) using Softmax layer, CNN + TL with SVM classifier (CNN+TL+SVM), Resnet-50 with transfer learning (Resnet-50+TL) with Softmax layer, and Resnet-50+TL with SVM classifier (Resnet-50+TL+SVM) are compared. Using different settings, the classification performances are analyzed. Finally, outcomes are benchmarked with other state-of-the-art models on the Figshare dataset to show the effectiveness of the proposed approach.

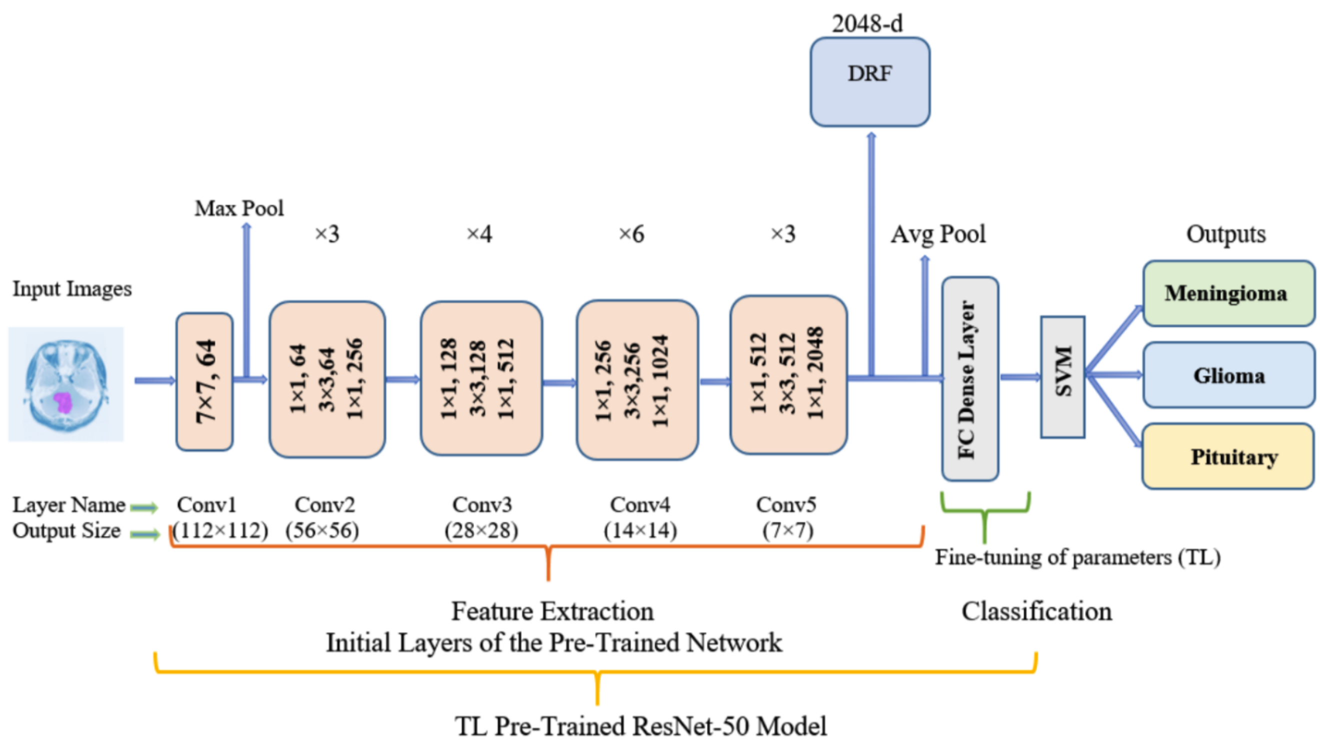

Figure 6. Proposed Resnet-50 Architecture with TL, fine-tuning approach and SVM

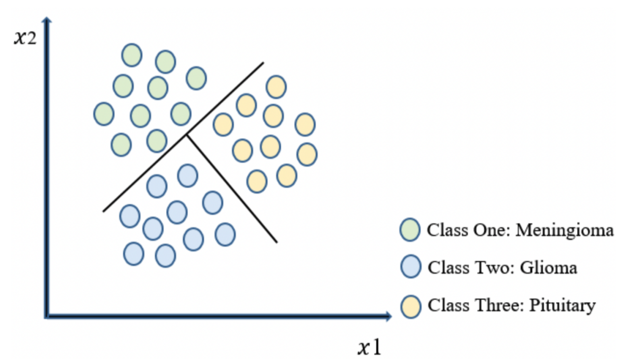

Figure 7. SVM for Multi-Class Classification

A. Experimental Setup

The experiment is implemented and evaluated for the proposed TL-based model for brain tumor classification in Phyton functioning Keras, TensorFlow, and Scikit-Learn libraries and Jupyter tool in Anaconda software. The running code has been implemented by the Google Colab platform. First the implemented four models are trained on the Figshare dataset. For this purpose, the Figshare dataset is divided into training and testing with 75% and 25% ratios respectively. The hyper-parameters of these four models are shown in Table III. For methods that use SVM classifier, rbf kernel is utilized with gamma learning rate. For methods that use deep transfer learning without a separate SVM classifier, the Adam optimizer has been applied with categorical cross-entropy as the loss function. For fair comparison, all methods have the same epoch of 30 and batch size of 32. In the following sections, results on the accuracy, precision, recall, and f-scores are summarized.

B. Classification Metrics - Accuracy, Precision, Recall and F-Score

The classification accuracy is capable of correctly predicting the correct class of the test image. Improving accuracy in any brain tumor classification model is crucial for both doctors and patients. It can help doctors to diagnose the patient's condition with the type of tumor. It can also help to increase the life expectancy of the patient by early detection of the tumor type. Accuracy is the main performance measurement metric for classification. It is the number of accurate predictions divided and multiplied by 100 by the total number of predictions.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + PN} \times 100 \qquad (1)$$

Where TP and TN are results generated once the system accurately classifies the positive class and the negative class, sequentially. Although FP and FN are results generated when the system inaccurately classifies the positive class and the negative class, respectivel.

If there are imbalanced accuracy observations for different classes in the data set, then the classification accuracy does not a proper approach to a performance measure? In this situation, for validation, class-specific performance

Model Name	Learning Rate	Epoch	Batch size	Parameters
CNN+TL	0.01	30	32	3,869,639
CNN+TL+SVM	0.01+'gamma':[1e-3, 1e-5]	30	32	3,869,639
ResNet-50+TL	0.0001	30	32	23,587,523
ResNet-50+TL+SVM	0.0001+'gamma':[1e-3, 1e-5]	30	32	23,587,523

TABLE III. Hyper-parameters of Deep Learning Models

metrics should be required. Precision is a part of metrics that are described such as:

$$Precision = \frac{TP}{TP + FP} \times 100 \quad (2)$$

For each class of the model, the above mathematical formula is applied and validated for the performance. Precision gives how the model accurately predicts the class of a certain class. If the precisions of whole classes are high, after that it could be deduced that the system has trained well for all classes equally.

Another significant metric is Recall, described as the fragment of observation points from a category that is successfully expected by the model.

$$Recall = \frac{TP}{TP + FN} \times 100 \quad (3)$$

F-score is another significant measure to combine precision and recall in a single metric. F-Secure's mathematical equation meaning is described as:

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (4)$$

C. Training and Validation of CNN Models

This work has four different settings with a fine-tuning strategy; CNN+TL, CNN+TL+SVM, ResNet-50+TL and ResNet-50+TL+SVM. These different settings are implemented in Python using Google Colab platform. To visually assess the training performance of these four settings, training vs validation accuracy and training vs validation loss graphics are illustrated as follows. In Figures 8 and 9, examples of train-validation accuracy and train-validation loss graphics for shown for CNN+TL respectively. Figure 8 shows that train-validation accuracy stays stable and increases with the increasing epoch size. The total number of epochs was 30. Figure 9 illustrates that validation loss reaches a stable condition after epoch 20. Example train-validation accuracy and train-validation loss graphics are also demonstrated in Figures 10 and 11 for Resnet-50+TL. For this replication, 30 epochs were used. Figure 10 shows similar train-validation patterns compared to CNN+TL (Figure 8). Whereas, in Figure 11, it is illustrated that train-validation loss graphic of Resnet-50+TL is more unstable compared to CNN+TL (Figure 9).

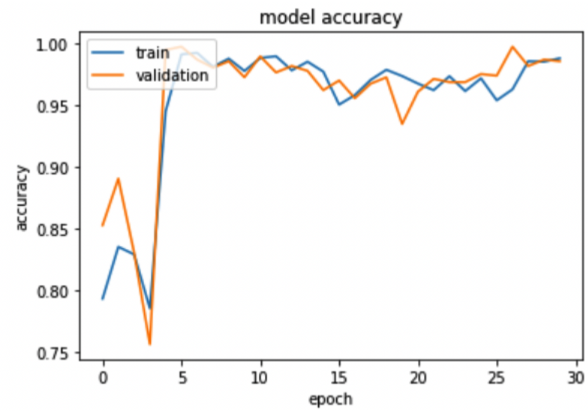

Figure 8. Train Accuracy vs Validation Accuracy using CNN + TL

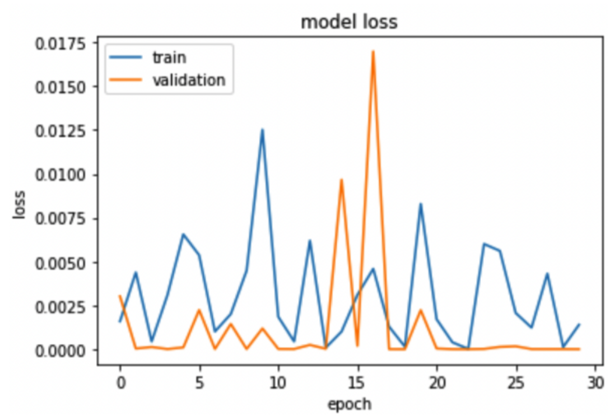

Figure 9. Train Loss vs Validation Loss using CNN + TL

D. Precision, Recall and F-Score Comparisons and Discussions

On the other hand, precision, recall, and f-scores for different transfer learning settings are benchmarked. Table IV demonstrates CNN+TL, Table V shows CNN+TL+SVM. Results show that CNN+TL with fine-tuning has better average Precision (99.67%), Recall (99.76%) and F1-score (99.71%) compared to CNN+TL+SVM with fine-tuning. However, CNN+TL+SVM also achieves very high performance except the fact that Pituitary tumor class classification has a minor performance decrease for Precision, which affects the overall performance. In summary both CNN+TL and CNN+TL+SVM achieve very good results.

Table VI demonstrates ResNet-50+TL and Table VII

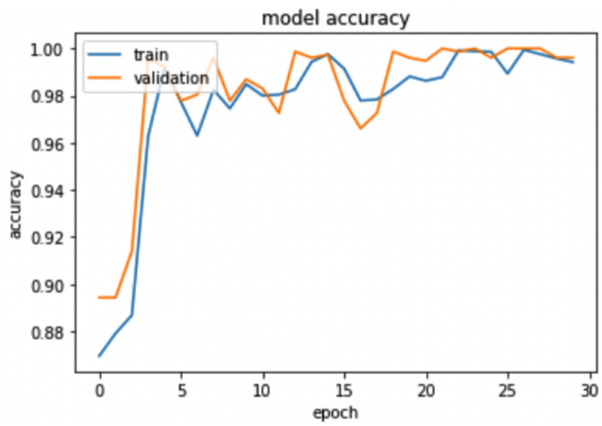

Figure 10. Train Accuracy vs Validation Accuracy using ResNet-50+TL

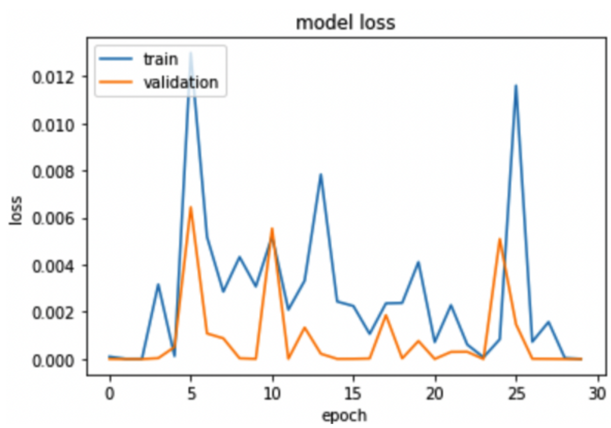

Figure 11. Train Loss vs Validation Loss using ResNet-50+TL

Classes	Precision%	Recall%	F1-score%
Meningioma	99.45	100.00	99.72
Glioma	100.00	99.72	99.86
Pituitary tumor	99.55	99.55	99.55
Average	99.67	99.76	99.71

TABLE IV. The Precision, Recall, F-Score using CNN+TL

Classes	Precision%	Recall%	F1-score%
Meningioma	100.00	98.33	99.16
Glioma	100.00	99.45	99.72
Pituitary tumor	97.82	100.00	98.90
Average	99.27	99.26	99.26

TABLE V. The Precision, Recall, F-Score using CNN+TL+SVM

Classes	Precision%	Recall%	F1-score%
Meningioma	98.82	87.89	93.04
Glioma	99.12	96.28	97.67
Pituitary tumor	87.21	99.12	92.78
Average	95.05	94.43	94.50

TABLE VI. The Precision, Recall, F-Score using ResNet-50+TL

Classes	Precision%	Recall%	F1-score%
Meningioma	100.00	70.00	82.35
Glioma	100.00	90.83	95.20
Pituitary tumor	71.84	100.00	83.61
Average	90.61	86.94	87.05

TABLE VII. The Precision, Recall, F-Score using ResNet-50+TL+SVM

shows ResNet-50+TL+SVM results for precision, recall, and f-scores results. ResNet-50+TL with fine-tuning performs significantly have better average Precision (95.05%), Recall (94.43%) and F1-score (94.50%) compared to the performance of ResNet-50+TL+SVM with fine-tuning. In ResNet-50 based TL methods, especially Pituitary tumor class affects the performance; for ResNet-50+TL, it has a Precision of 87.21% and for ResNet-50+TL+SVM, it has a precision of 71.84%. Another observation is that F1-score rate of ResNet-50+TL+SVM decreases considerably when SVM classifier is employed. When ResNet-50+TL (using different classifiers) and CNN+TL based methods are compared (Table IV and Table V), it is observed that CNN+TL with fine-tuning performs significantly better for all metrics.

E. *Accuracy Comparisons and Discussions*

Accuracy classification is the most important performance metric for a category, which provides a percentage of the classifier's true predictions. The accuracy is presented for the classification achieved in four different settings in the experiment (Table VIII); CNN+TL, CNN+TL+SVM, ResNet-50+TL and ResNet-50+TL+SVM. The difference of the proposed approach can be summarized as follows: Batch normalization is applied to input images within the training process and fine-tuning is applied in the last layers, where four dense layers are applied with ReLU activation function. The last dense layer is followed by the softmax activation function. CNN+TL with Softmax classifier achieves an accuracy of 98.56%. In another setting, SVM is used as a classifier with CNN+TL (CNN+TL+SVM) for the multi-class classification, where Softmax features are given to multi-class SVM. It is observed that CNN+TL+SVM improves the accuracy to 99.35%. In another setting, ResNet-50+TL with fine-tuning is tested. Dense layers (fine-tuning) are applied and followed by Softmax activation

Model Name	Model Accuracy (%)
CNN+TL	98.56
CNN+TL+SVM	99.35
Resnet-50+TL	99.61
Resnet-50+TL+SVM	88.38

TABLE VIII. Comparison of models

function. ResNet-50+TL achieves an accuracy of 99.61%. The ResNet-50 is a powerful model that is used merely for classification. Generally ResNet-50 requires huge datasets to run. With the applied fine-tuning strategy, the last layers of the CNN model is replaced in order to run on a small dataset like Figshare. Finally, when an SVM classifier is used together with ResNet-50 (ResNet-50+TL+SVM), accuracy is dropped to 88.38%. The deviated accuracy is caused by the fact that ResNet-50 and SVM are not compatible due to the size of their networks. To summarize, training of large networks like ResNet-50 require huge computational resources. Whereas using the proposed batch normalization for inputs, fine-tuning and SVM classifier with a custom simple CNN model, very competitive results can be achieved in much shorter training times (Table VIII).

F. Results with Confusion Matrix

Confusion matrixes are used to illustrate the classification performance in different classes, where each column shows the true label and each row shows a predicted label. A normalized confusion matrix is the outcome of the values split by the number of characteristics in each label for an improvement optic explanation of which label is being led to classify improperly. The confusion matrix is applied to estimate the performance of method classifications; within it, the predicted label is the number of classes. In this work, three classes of tumors are classified; 0 represents Meningioma, 1 represents Glioma and 2 represents Pituitary. Confusion matrix for CNN+TL+SVM is shown in Figure 12. It is observed that test images are classified into the correct class with very high accuracy. In Figure 13, confusion matrix for ResNet-50+TL+SVM is shown. It is seen that Pituitary class is confused with Meningioma and Glioma classes. By visual examination, CNN+TL+SVM performs better.

G. Comparison of the Results with Related Work on the Figshare Dataset

Since different methods published their results on the Figshare dataset using the same evaluation procedures, the results are compared with them as illustrated in Table IX. SVM was an important approach to the BoW feature set design among the studies that used up hand-crafted models [16]. The outcomes have improved by employing deep learning methods and the operation of CNN elements [12, 19-24]. CNN based methods [12, 19, 20, 21, 24] perform in the range of 84% - 96%. Deep transfer learning based methods [22, 23, 25] that use Resnet-34, VGG19 and ResNet-101 respectively achieve performances in the range of 93% - 95%. The motivation of our work is to

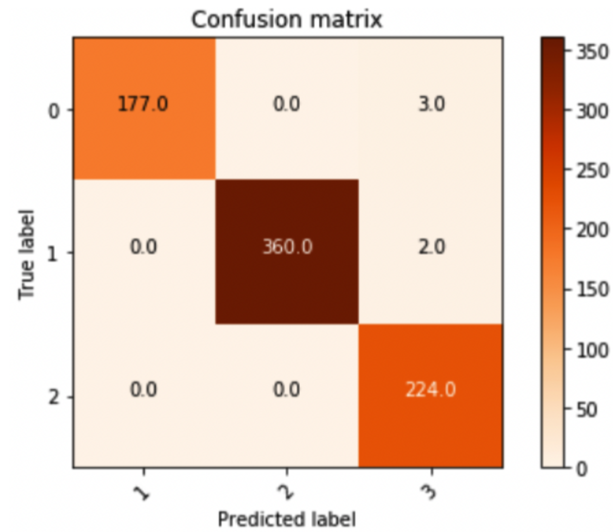

Figure 12. Confusion Matrix using CNN+TL+SVM

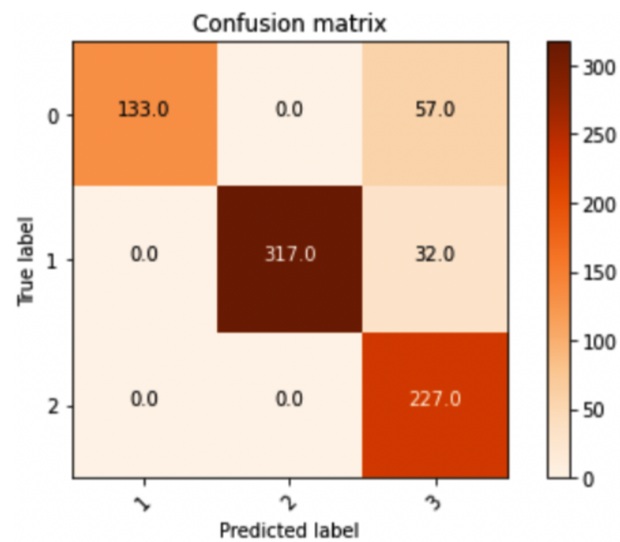

Figure 13. Confusion Matrix using ResNet-50+TL+SVM

improve the classification performance on the Figshare dataset and we propose a novel deep transfer learning model using a fine-tuning strategy. The results in Table IX show that the proposed deep learning models improve the state-of-the-art. Proposed CNN+TL with fine-tuning and SVM classifier, and ResNet-50 with fine-tuning and Softmax classifier achieves one of the best results among the related works. In particular, when the proposed method uses CNN+TL as feature extraction, Softmax as the model classifier, it achieves an accuracy of 98.56% after going through fine-tuning procedure. While CNN+TL with SVM with fine-tuning, archives a higher accuracy of 99.35%. On the other hand, when pre-trained ResNet-50+TL is applied with Softmax and fine-tuning strategies, the accuracy level has improved to 99.61%. The reason for this improvement

Authors	Features	Model Classifier	Dataset	Accuracy (%)
Cheng et al. (2015) [16]	BoW	SVM	Figshare	91.28
Ismail & Qader. (2018) [17]	WDT & Gabor	BPNN	Figshare	91.90
Afshar et al. (2018) [18]	CapsNet	CapsNet	Figshare	86.56
Pashaei et al. (2018) [19]	CNN	ELM	Figshare	93.68
Abiwinanda et al. (2018) [20]	CNN	CNN	Figshare	84.19
Anaraki et al. (2019) [21]	CNN-GA	CNN-GA	Figshare	94.20
Liu et al. (2019) [22]	ResNet-34	Gap	Figshare	95.00
Swati et al. (2019) [23]	VGG19 (TL)	VGG19(TL)	Figshare	94.82
Ghosal et al. (2019) [25]	ResNet-101	CNN	Figshare	93.83
Deepak and Ameer (2020) [12]	CNN	SVM	Figshare	95.82
Togacar et al. (2020) [24]	CNN	CNN	Figshare	96.05
Proposed Method CNN+TL with fine-tuning		**Softmax**	**Figshare**	**98.56**
Proposed Method CNN+TL with fine-tuning		**SVM**	**Figshare**	**99.35**
Proposed Method ResNet-50+TL with fine-tuning		**Softmax**	**Figshare**	**99.61**
Proposed Method ResNet-50+TL with fine-tuning		**SVM**	**Figshare**	**88.38**

TABLE IX. Comparison with the Related Work on the Figshare Dataset

is that the ResNet-50 consists of a powerful network that gives better feature extraction performance, although it takes longer to train the network. However, using ResNet-50 with SVM can significantly decrease the accuracy outcome down to 88.38%. The deviated accuracy is caused by the fact that ResNet-50 and SVM are not compatible due to the size of their networks which seriously decreases the accuracy outcome. In any case, the proposed TL based fine-tuning strategy provides the best results among other related works.

5. Conclusions and Future Work

A brain tumor is a more destructive illness, heading to the lowest survival span at the largest degree. Any wrong diagnosis of tumors on the brain makes misunderstanding of medical intervention and decreases patients' chances of survivability. The specific detection of brain tumors is a crucial point for adequate care planning to cure patients with brain tumor disease and improve their existence. For the classification of brain tumors from MRI images, Deep Learning techniques are recommended.

The proposed method has been trained on the Figshare dataset. Different transfer learning settings were compared using a proposed convolutional neural network architecture and ResNet-50 pre-trained for feature extraction. Transfer learning techniques are applied to fine-tune each model separately. Furthermore, for the classification of different types of brain tumors meningioma, glioma, and pituitary, SVM is applied.

This work aims to make the accuracy of the classification better, prevent overfitting, and speed up the training time. This is found that the proposed CNN architecture %) with less number of parameters and faster training times. In addition, the fine-tuning of transfer learning parameters improves the accuracy of the Resnet-50 model as well (99.61%). The proposed transfer learning-based solutions can also be applied to other medical image domains such as breast, lung, and liver tumor classification.

As a future extension for this study, other types of pre-trained models can be investigated such as AlexNet, GoogleNet, DenseNet, and other sorts of ResNet or VGG for segmentation, detection, and classification of brain tumors. In addition, BraTS dataset can be used for brain tumor detection and grading using deep transfer learning.

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