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A Feature Fusion Based System for Brain Tumor Classification

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***Abstract*—Classifying brain tumours is an exclusive and difficult task in clinical image analysis. Radiologists could reliably detect tumours using machine learning algorithms without extensive surgery. However, several difficulties arise, including difficulty locating a competent specialist in identifying brain malignancies using images using deep learning models and the main issue in the erection of the most effective deep learning system for diagnosing tumour cells. We used deep learning and adaptive algorithms to build a sophisticated and incredibly accurate system with feature fusion to automatically categorize brain tumors. The proposed framework extracts deep features from CNN architectures with varying depths and designs. The highest-performing CNN architectures' features are then fused to form a single vector classified using SVM and KNN. The novel vector obtained the highest accuracy of 92% via the feature fusion method. Therefore, the suggested framework can be successfully used in clinical settings to categorize three different forms of tumors, namely gliomas, meningiomas, and pituitary tumors, from medical imaging.**

***Keywords*—brain tumor classification, deep learning, feature fusion**

I. INTRODUCTION

The vital organ of the human body responsible for making decisions is the brain, which is housed in a sturdy skull. A mass of abnormal cells that forms in the brain is known as a brain tumour. Significant problems will arise with any expansion in this area. Brain tumors are among the world's most lethal tumor forms. The tumor results in death or irreversible brain damage. In 2019, there were over 86,000 new instances of brain tumors identified. 17,000 persons have passed away from this illness as of 2019 [1].

Additionally, according to the location and severity of the tumor, three groups of brain tumors—gliomas, meningiomas, and pituitary tumors—have been established. The tumor known as a glioma develops from a type of brain stem cell that is typically immature and mutates, causing it to grow abnormally. Contrarily, pituitary tumors are discovered in the center of the skull, behind the eyes, while meningiomas develop from the membranes surrounding and protecting the brain and central nervous system. The three forms of tumors differ in their location, surrounding tumor tissue, and intensity. To classify three different types of tumors as malignant or benign, it is crucial to look at their distinctive characteristics. Most meningiomas and pituitary tumors are benign, while high-grade glioma tumors are typically malignant. Due to these various tumor characteristics, accurate brain tumor type classification is crucial for clinical diagnosis and efficient tumor treatment evaluation [2].

Technology and the quick development of brain imaging techniques have always been crucial in assessing and concentrating fresh perspectives on the structure and operation of the brain. Diagnosing a brain tumor enhances treatment results and patient survival chances. However, it might be challenging to manually analyze the numerous magnetic resonance imaging (MRI) images that are generated in a medical facility. This directly leads to the need for more accurate computer-based tumor identification techniques. In recent years, traditional machine-learning techniques that can automate this procedure have been the subject of extensive study. The adoption of deep learning techniques as a more reliable and accurate way to diagnose brain cancers has recently attracted renewed interest. The process of image processing is widely employed in the field of medical science to enhance the stages of early diagnosis and therapy. However, traditional ML-based frameworks require human intervention, relying on hand-engineered feature extraction and classification. Hence, DL based methods are a rage today due to their exceptional performance [3].

Artificial intelligence (AI) has a subfield known as deep learning (DL). It allows computational models to learn new things and develop their capacity to function like humans. It has several levels that serve as abstraction and information retrieval. DL, which includes fact-based analytical modelling, is a key element of data science. It aids data scientists in their efforts to gather insightful data from huge datasets. Deep learning produces the optimum performance and accuracy by utilizing a vast array of datasets. It also facilitates and streamlines the process of data analysis. A convolutional neural network (CNN) is the most common technology used to recognize patterns. CNN helps interpret digital visuals. CNN separates images into picture elements and labels and marks each component. The items are then classified using training models according to these indicators [4].

Recent human efforts to enhance computer-aided medical diagnosis yield better results. For instance, an approach presented by Gupta et al [5] used an ANN in conjunction with canny edge detection that were used to remove edges from images. These preprocessed images were then converted from RGB to greyscale and in the end classified via an ANN. A hybrid strategy was created by Kumar et al. [6] for BT detection and categorization. The proposed approach comprised feature reduction by PCA and discrete wavelet transform of MR images. Utilizing a kernel SVM trained with the reduction feature, the suggested hybrid outperformed traditional DL techniques by increasing accuracy and lowering root mean square error. Rammurthy et al. [7] proposed a new DL-based BT detection technique termed as Whale Harris Hawks optimization by fusing the whale optimization algorithm (WOA) with the Harris hawks optimization (HHO) algorithm. Prior to classification using the suggested Whale Harris Hawks optimization, cellular automata is used to segment the tumors in the photos, and WHHO is used to extract various properties such as size, variation, mean, and kurtosis. The accuracy of the proposed technique peaked at 81.6%. For three publicly accessible BT datasets, Amin et al.'s [8] automatic detection and classification method is presented. They segment the area of interest using various morphological procedures and pre-processing methods. Additionally, each candidate's lesion characteristics, including lesion intensity, texture, and form, are retrieved and then classified using an SVM. A brain tumor classification system that combines machine learning and deep learning techniques is presented in [9]. They used the words glioma, meningioma, and pituitary to designate the three different categories of brain tumors. They altered the Google Neural Network model using transfer learning to recover the deep features. Then, the obtained features are categorized using SVM, KNN, and SoftMax. A multiclass brain tumor classification approach was developed by Yazdan et al. [10]. The experimental findings demonstrated that the proposed multi-scale CNN model outperformed ResNet and AlexNet while consuming fewer resources. The system resulted in 90% accuracy. The existing algorithms have several limitations, including complex algorithms and use of binary databases. In this study, we use DL methods to offer a fully automated brain tumor classification methodology. The following are the study's contributions:

- On a cutting-edge database that contains MRI scans of three different tumor types—glioma, meningioma, and pituitary—the suggested framework is trained and validated.
- The presented framework uses the concept of feature fusion, combining multiple features extracted from different sources or modalities into a single representation. This process helps improve a system's overall performance by leveraging information from different sources.
- The proposed algorithm extracts features from heterogenous CNN architectures and then combines them together to increase robustness of the system. This aids in better feature representation as a variety of varying features are combined together and supplied to classification algorithm for prediction.
- The presented approach succeeded in achieving highest accuracy of 92% on Figshare database.

The rest of the document is structured as follows: The proposed methodology is discussed in Section II. Section III presents outcomes obtained from proposed method and presents a comparison with existing studies. Whereas, conclusion and future work is presented in Section IV.

II. PROPOSED FRAMEWORK

In this paper, we suggest a completely automated brain tumor classification approach employing feature extraction using well-known deep learning algorithms and fusion of those features. Initially, the database is prepared by applying min-max normalization technique to scale the intensities of MRI images. Then famous CNNs are used as feature extractors. These features are then fused together and classified via SVM and KNN classifiers. The workflow diagram of suggested framework is shown in *Figure 1*

A. *Database Acquisition & Preprocessing*

The study is conducted on MR images acquired from Figshare database. The database includes 233 patients' 3064 T1-weighted MR pictures in three planes, i.e., axial, coronal and sagittal. The images are stored in. mat format and, hence are preprocessed by applying min-max filters to scale the intensities between (0 and 1). The preprocessed images are then resized according to the input size of CNN architectures. The dataset is divided into 70% train and 30% validation samples. Preprocessing of MR images is shown in *Figure 2*. Whereas tumor sample images collected from the database are depicted in *Figure 3*.

A. *Deep Feature Extraction, Fusion & Classification*

Although artificial intelligence (AI) systems are currently outperforming humans in certain key areas like voice and image recognition, our brains are still significantly more capable of handling most of the activities that we encounter daily. One of DL's key advantages is its capacity to extract higher-level features from the raw input data, which was originally inspired by biological models of computing and cognition in the human brain. Deep learning-based algorithms exhibit high efficacy in inpainting tasks thanks to the quick growth of deep learning in computer vision. Deep learning-based algorithms have much better results than classical algorithms because they can capture higher-level information from the data [11, 12].

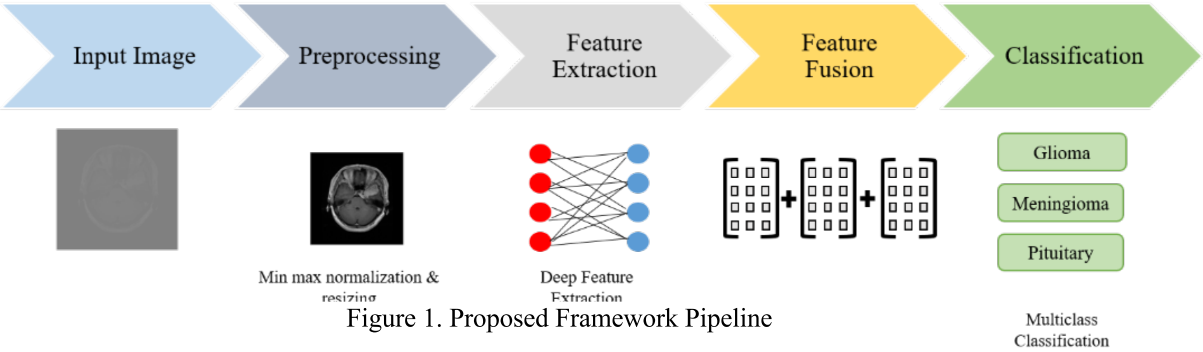


Figure 1. Proposed Framework Pipeline

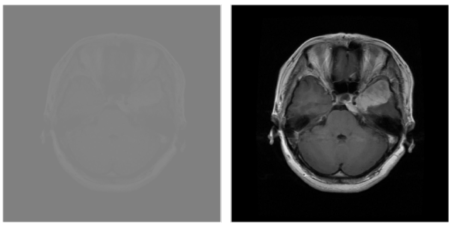


Figure 2. MRI Preprocessing

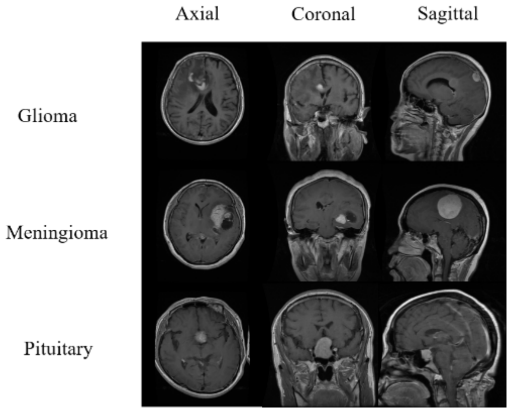


Figure 3. MRI Samples

CNN is a popular deep-learning architecture that draws inspiration from how living things naturally sense their surroundings. The foundational study creating the present CNN framework was published in 1990 by LeCun et al.[13-18], and it was later enhanced in. LeNet-5, Handwritten digits might be categorized using a multi-layer artificial neural network they developed. LeNet-5 is a multi-layer neural network that, like other neural networks, can be developed via the backpropagation method. Several techniques have been created since 2006 to get around the challenges associated with training deep CNNs. Most significantly, Krizhevsky et al. [14, 19-24] introduced a traditional CNN design and demonstrated substantial advancements over earlier approaches to the image classification challenge. LeNet-5 and AlexNet-5 share a similar overall architecture, but the latter has a deeper structure [15]. Many initiatives to enhance AlexNet's performance are VGG19 [16], ResNet18 [17] and DenseNet201 [18].

In this phase, we extract deep features from well-known CNN architectures such as AlexNet, ResNet18, DenseNet201 and VGG16. We chose architectures of varying designs to extract diverse features that will aid in proper classification. The CNN architectures with varying depths and designs extract both low-level and high-level features, including changes in colour intensities, edges, location of pixels, shapes, etc. that will not only help in distinguishing between types of tumors but also determine normal and abnormal pixel values. We later fuse the highest-performing feature vectors. The novel feature vector is more robust and effective in determining the tumor types. This is because the single feature vector from independent CNNs when combined, diversifies the vector space and increases the discrimination abilities of the framework. Original and novel features are categorized using SVM and KNN. These state-of-the-art classifiers have proven the results in the field of ML. Hence, we fed all the features to these classifiers for accurate and effective classification of brain tumors from medical images. The process of feature fusion is illustrated in Fig*ure 4*.

III. RESULTS AND DISCUSSION

A. Evaluation Metrics

Evaluation metrics are crucial for measuring and evaluating the efficacy of various systems or processes. These metrics can offer insightful information about a system's performance, enabling organizations to make defensible choices about increasing effectiveness and efficiency. Organizations can compare various systems and processes using these indicators to find the best solutions for their needs. Measuring the success or failure of a system or process may be done clearly and thoroughly thanks to evaluation metrics, which is one of their main advantages. Metrics for evaluation can serve as a foundation for continual improvement, another benefit. We measured our suggested framework's accuracy, precision, recall, and f1-score to assess its performance. Equation (1) through Equation (4) calculates the metrics. Accuracy is one of the frequently employed metrics to assess the effectiveness of automated systems. However, more than this alone as a metric is needed to prove the framework's robustness in unseen scenarios. Hence, precision and recall are very useful as well. Whereas F1-Score associations precision and recall metrics are widely beneficial in imbalanced datasets.

$$Accuracy = \frac{tp+tn}{tp+tn+fp+fn} \tag{1}$$

$$Precision = \frac{tp}{tp+fp} \tag{2}$$

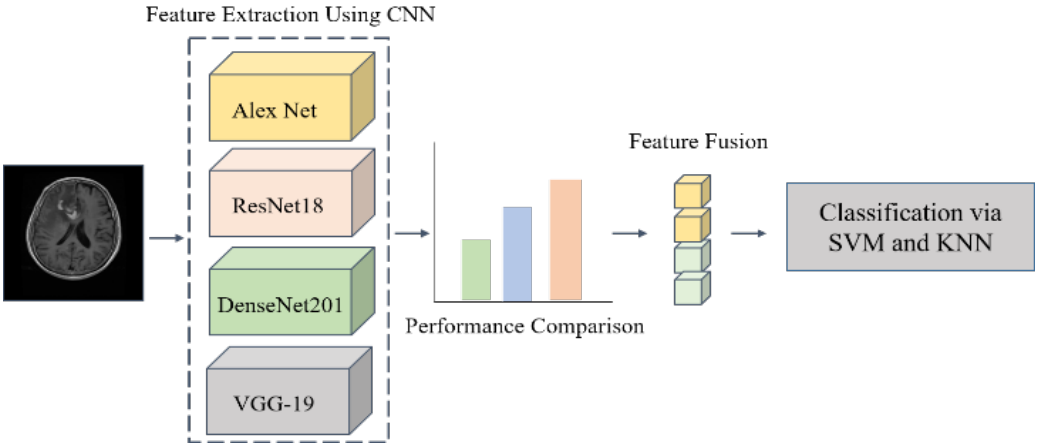


Figure 4. Feature Fusion Process

$$Recall = \frac{tp}{tp+fn} \quad (3)$$

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

B. Proposed Method Results

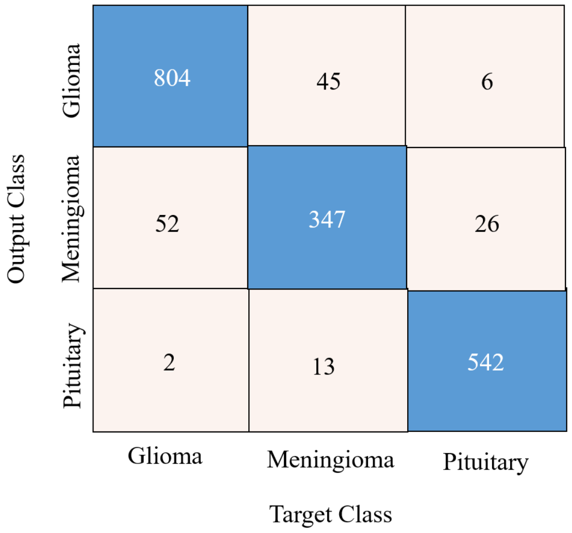
The proposed framework achieved a maximum accuracy of 92% via deep feature fusion. The results from independent CNNs are depicted in

TABLE *I*. The highest-performing features i.e. AlexNet and DenseNet201, are combined to form a novel vector. The novel vector is then classified using SVM and KNN.

TABLE I. ACCURACY % FROM INDEPENDENT VECTORS

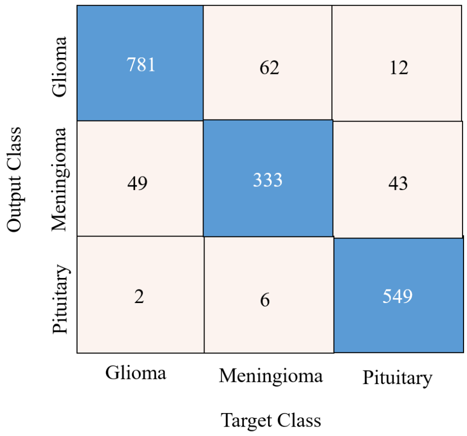
Feature Vector	**SVM**	**KNN**
AlexNet	89	86.9
ResNet-18	89	89
DenseNet201	88	87.6
VGG-16	85.3	86.3

The fused vector attained the highest performance of 92.2% via SVM and 91% via KNN. Confusion matrices obtained from SVM and KNN are depicted in Figure 5 and Figure 6. A way to evaluate the effectiveness of a classification algorithm is to create a confusion matrix. The rows match the real classes that the results were meant for. The columns are a representation of our predictions. It is straightforward to spot incorrect forecasts with this table. The results depict the robustness and performance of the proposed strategy; hence, it can be used to use MR images for real-time diagnosis and detection of brain tumors.



	Glioma	Meningioma	Pituitary
Glioma	804	45	6
Meningioma	52	347	26
Pituitary	2	13	542

Figure 5. SVM Confusion Matrix



	Glioma	Meningioma	Pituitary
Glioma	781	62	12
Meningioma	49	333	43
Pituitary	2	6	549

Figure 6. Confusion Matrix Obtained from KNN

Precision, recall, and f1-score results from additional metrics are displayed in Figure 7. The ability of a test to determine whether or not a specific condition occurs is measured by the area under the ROC curve (AUC). A test with a perfect AUC of 1.0 is said to have perfect discrimination, whereas a test with a 0.5 AUC is said to have poor discrimination. In Fig*ure 8*, the ROC curves for gliomas, meningiomas, and pituitary tumors are displayed. ROC curve is a model performance measure widely used in classification systems. The curve can help to measure how well a model discriminates between positive and negative samples. ROC curves can help to determine the optimal threshold value for a model. By visually inspecting the curve and selecting a point that maximizes sensitivity and specificity or AUC, users can select the threshold value that maximizes the performance of the model. Unlike other evaluation metrics, ROC curves are less sensitive to imbalanced data or changes in class distributions. Therefore, ROC curves are often used to evaluate model performance on datasets with changing class balance. The curves, in this case, show that the suggested strategy for classifying brain tumors performs well. As a result, it may be quickly and easily used in clinical settings to identify tumors at an early stage.

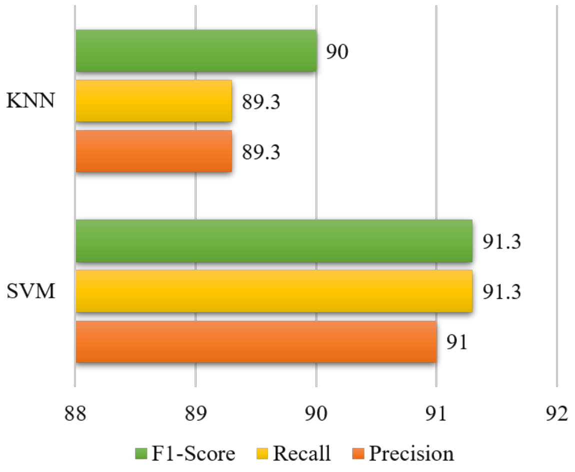


Figure 7. Results in terms of Precision, Recall and F1-Score

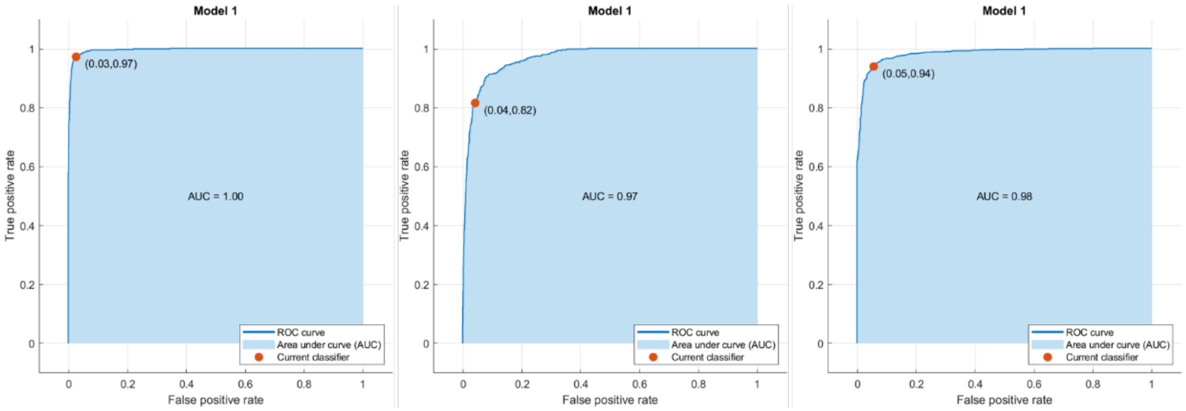


Figure 8. ROC Curves

Figure 9 compares the performance of the suggested strategy with the prevailing method. The table shows that the suggested technique achieved a maximum performance of 92.2% using the fusion method—for example, Yazdan et al. [10] deployed various CNN architectures for the classification of tumors. Their system peaked at 90% accuracy. A WHHO-based system was proposed by Rammurthy et al. [7] that resulted in 81.6% accuracy. Our feature fusion-based framework achieved the highest accuracy of 92%.

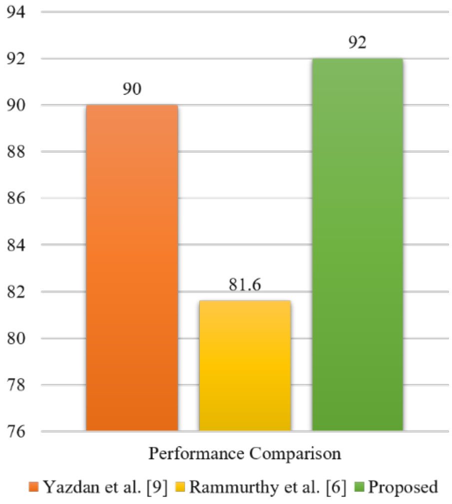


Figure 9. Comparison with Existing Systems

IV. CONCLUSION AND FUTURE WORK

The broad category of intracranial tumors known as "brain tumors" is extremely deadly and sick. Today, radiologists may utilize software identified as computer-aided detection and diagnosis (CADe and CADx), which uses artificial intelligence and computer vision to analyze radiological and pathology images to help diagnose human disease in various body regions, which includes the detection of tumors. Traditional methods, however, require manual feature extraction, which is error-prone and time-consuming. Hence a complete automated system is necessary to develop an effective and robust system.

Brain tumor classification is crucial in medical imaging to aid in diagnosis and treatment planning. With advancements in deep learning techniques, various methods have been proposed to classify brain tumors from MRI scans. One of the most popular deep learning techniques for brain tumor classification is the Convolutional Neural Network (CNN). To effectively classify brain tumors, CNNs utilize several layers of convolutional filters to learn the most relevant features from the MRI scans. With the increasing availability of large datasets and computing resources, deep learning methods are expected to continue to improve and be valuable tools for brain tumor classification.

This paper presents a novel tumor classification system using the feature fusion method. The MRI images are initially preprocessed, then features are extracted using CNN architectures such as AlexNet, VGG-19, ResNet18 and Densenet201. The features are classified using SVM & KNN. The highest-performing features are then combined in a single vector. The novel vector resulted in a maximum accuracy of 92%. The results prove the system's performance for tumor detection and classification. Hence, the framework can be effectively deployed in clinical setups for real-time diagnosis. In future, we will extend our framework to other databases to include more tumor types.

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