A Robust Hybrid Convolutional Network for Tumor Classification Using Brain MRI Image Datasets

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Abstract*—Brain tumour detection is challenging for experts or doctors in the early stage. Many advanced techniques are used for the detection of different cancers and analysis using different medical images. Deep learning (DL) comes under artificial intelligence, which is used to analyse and characterisation medical image processing and also finds the classification of brain cancer. Magnetic Resonance Imaging (MRI) has become the keystone in brain cancer recognition and the fusion of advanced imaging methods with cutting-edge DL models has exposed great potential in enhancing accuracy. This research aims to develop an efficient hybrid CNN model by employing support vector machine (SVM) classifiers to advance the efficacy and stability of the projected convolutional neural network (CNN) model. Two distinct brain MRI image datasets (Dataset_MC and Dataset_BC) are binary and multi-classified using the suggested CNN and hybrid CNN-SVM (Support Vector Machine) models. The suggested CNN model employs fewer layers and parameters for feature extraction, while SVM functions as a classifier to preserve maximum accuracy in a shorter amount of time. The experiment result shows the evaluation of the projected CNN model with the SVM for the performance evaluation, in which CNN-SVM give the maximum accuracy on the test datasets at 99% (Dataset_BC) and 98% (Dataset_MC) as compared to other CNN models.

***Keywords*—CNN; SVM; MRI images; brain tumor; deep learning**

I. INTRODUCTION

Cancer cells are abnormal cells that disturb or damage the normal life of the human body. These cells spread rapidly and infect the other cells in the human physique. The detection of these cells in the early stage increases the survival rate of human life. Doctors can find these cells but not in the early stage which decreases the mortality rates of humans. Advanced techniques have come like artificial intelligence which can be used in medical science or medical image processing (like MRI, CT X-ray etc) to detect, segment and classify any disease (brain cancer, lung cancer, oral cancer, bone fracture etc) in different parts of the human physique.

MRI plays a key part as compared to other imaging modalities due to the non-invasive characterization of brain tumors. It is the capability to provide complete images of the brain's anatomy, along with the distinct characteristics of different cancer types, that makes it an indispensable tool for clinicians. A traditional approach to brain tumor classification relied on histopathological analysis of tissue samples obtained through an invasive procedure. Though histopathology is still significant, it has problems such as patient risks and sampling mistakes. These matters are addressed with MRI, which delivers a non-invasive, complete image of the entire brain, simplifying precise preoperative diagnosis and handling forecasting.

To discriminate and categorize many forms of brain cancer, including gliomas, meningiomas, and pituitary tumors, MRI is a crucial tool. When combined with sophisticated MRI methods, CNN enables more precise classification, enabling doctors to make up-to-date conclusions regarding patient supervision.

Brain cancer is a hazardous and irregularly fatal disease for which early and correct detection is important to actual action. By combining their individual advantages, convolutional neural networks and traditional MRI imaging can be used to distribute more correct classification.

Artificial intelligence (AI) methods have renovated medical imaging and significantly improved the detection of brain cancer. These methods, which are capable of large MRI image datasets, can identify complex patterns and features that recover the correctness of brain cancer classification. By using AI techniques in brain cancer discovery analysis, custom-made treatment options are developed and the diagnosis process is accelerated.

Current solutions are being accessible by the context-aware use of AI techniques in health care diagnosis. When utilizing MRI to diagnose brain tumors, it is necessary to conduct experimental work to detect the tumor, and classify it according to its grade, kind, and location. This approach has experimented with using a solo CNN model for brain cancer recognition on different datasets in the place of a different CNN model for the diverse classification task. Brain tumor identification and classification are possible with the CNN-based binary and multi-task classification system. However, most of the authors used different models for different classification systems.

II. RELATED WORK

The American Cancer Society estimates that as of 2021, 78,980 persons had acknowledged a brain cancer finding; of these, around 55 thousand were benign and 24 thousand were malignant [1]. Studies show that brain cancers are the foremost root of cancer worldwide [2].

Since various cells can cause different kinds of brain cancer, they are a diverse group. Essentially, lesions can be classified into binary categories: Primary lesions arise from inside the central nervous system, but secondary lesions can spread to other portions of the body and become brain metastases. The leading causes of illness and death worldwide are cardiovascular and cerebrovascular disorders. These conditions, which have a bigger financial burden than infectious diseases and harm society, start in childhood and can strike unexpectedly in maturity.

Medical image analysis often uses a variety of techniques to produce descriptions of the soft muscle in the human body. Medical professionals employ MRI images among them. It's a non-invasive method for accurately analysing imaging data of brain cancer in humans to assess the health of the patient [3]. Because of the tissue distinction stabilization and picture excellence determination, it is extremely applicable. The biology, chemistry, physiology, and genetic details of any brain disorder can be obtained from MRI pictures [4].

Brain cancer is well-defined by the World Health Organization (WHO) and controls all parts of the human body. This classification was revised in 2016. Broadly speaking, abnormal growth of a subset of brain cells is referred to as brain cancer. These cancers expose the brain's tissue to shrinkage, which causes massive harm to the brain's neuronal network and impairs the brain's ability to function [5-8]. Like any other kind of cancer, brain cancer can be classified as benign and malignant. While other types of brain tumors typically depend on the affected location like meningioma, glioma, and pituitary.

Utilizing the latest developments in science technologies to recover the precision of brain cancer identification in computer vision applications, merging (fusing) the images obtained from numerous imagery modalities. Artificial Intelligence [9] can be combined with these imagery modes to create finding systems. These kinds of systems can support doctors in refining the accuracy of early cancer recognition. Brain tumors can now be classified and identified using a variety of artificial intelligence techniques, including CNNs, SVMs, and artificial neural networks (ANNs) [10].

Authors proposed a CNN model such as VGG-(16 and 19) and InceptionV3 with Aquila optimizer. They classified brain tumor detection with an accuracy of 98.95% for the VGG-19 but testing accuracy is not given on the test dataset for this VGG-19 model [11]. Other authors proposed a CNN model with a ResNet50 architecture for the detection of brain cancers and found a correctness percentage of 98% in the MRI dataset [12].

The pre-trained CNN models were presented by the authors for the categorization of brain cancer from MRI pictures. They applied augmentation and image preprocessing like normalisation and resized the image 256x256 on the image dataset then found the maximum accuracy 96% in the VGG-16 model as compared to ResNet-50 and Inception V3 [13].

The analysis of the preprocessing stages for MRI image data enhances the detection accuracy in brain disease prediction. To propose a CNN pre-trained model, Authors suggest a VGG-16 pre-trained model for the categorization of multi-grade cancers in brain images [14].

The authors proposed an Inception-ResnetV2 model with grey wolf optimization and achieved 99.98% accuracy for brain tumor classification [15]. Another study done by authors proposes a CNN model with local constraints using a supervised k-nearest neighbour algorithm. They implemented two datasets for multi-class classification and found that CDLLC performed well as compared to other models VGG and GoogleNet [16].

A large number of academics looked into several algorithms for correctly and efficiently classifying brain tumors. Recently, DL methods have been extensively used to develop autonomous models that can speedily and efficiently detect brain cancer.

The authors conducted a study on brain tumor classification using four models S-CNN, InceptionV3, ResNet-50 and Xception on the two distinct brain image data sets. They trained data sets with or without principal component analysis and five-fold cross-validation. They found that Inception V3 and Xception models performed well as compared to S-CNN and ResNet-50 [17]. Another study was conducted by the authors for brain cancer classification using augmentation and transfer learning. The authors found an accuracy of 96.2% in the AlexNet model as related to the ResNet-50 and Inception-v3 models [18].

After the critical analysis from the literature review, existing models provide good accuracy on training data, but not for the test data. In this paper, design an optimal brain cancer detection model using a CNN approach to report the improvement of accuracy issues in the existing artificial diagnostic system, which classifies binary classification and also multi-classification on two different datasets using the single model.

III. OBJECTIVE

In the study, two main objectives are used for the detection of brain cancer:

1) First Focus on accuracy, mainly for testing datasets.

2) Second objective one CNN model is used for two different datasets for two different classifications.

IV. PROPOSED METHODOLOGY

The projected hybrid CNN model integrates the strengths of features learning from raw MRI images using convolutional layers with the interpretability and efficiency of traditional machine learning algorithms. The architecture consists of multiple convolutional, batch-normalization and max-polling layers for feature extraction, followed by densely connected layers and additional modules for specialized feature processing.

The proposed workflow, which utilizes two brain MRI image datasets: Database_MC and Database_BC. The projected CNN model incorporates common classification steps, including pre-processing, feature extraction, and classification. Various layer combinations, along with appropriate hyper-parameters, are used to progress a strong model that efficiently mitigates overfitting and bias in both datasets. By leveraging these techniques, the study aims to maintain the best classification accuracy while reducing computational requirements.

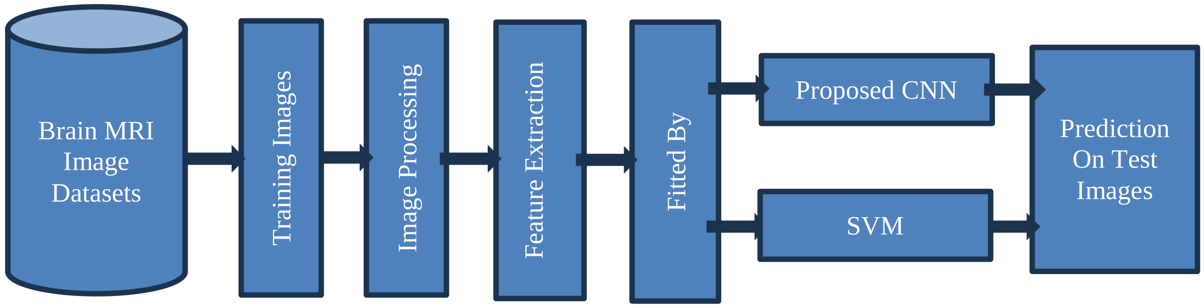

Fig. 1. Flow of proposed work.

The projected work is shown in Figure 1 for the classification.

The following steps are used in the algorithm to make the robust CNN and hybrid models classify the brain tumor MRI image datasets:

1) Collect the two datasets (Dataset_MC and Dataset_BC) of brain tumor MRI Grayscale Images from Kaggle

2) Apply image preprocessing like resize images (48x48) and normalize.

3) Encode all the images of the training and test dataset into labels (text to integers).

4) Extract feature using the proposed CNN model.

5) Train the model by applying the proposed CNN & hybrid CNN-SVM (Support Vector Machine) on the training dataset.

6) Classify the test dataset using the proposed CNN and CNN-SVM. Find the performance measures using the confusion matrix and classification report.

V. Data Collection

Brain MRI image datasets are downloaded from Kaggle. Dataset_MC [19] contains 7023 brain MRI images of four classes: glioma, meningioma, pituitary and nontumor, which is used in multi-classification. Dataset_BC [20] contains 3000 brain images of two classes yes (tumor) and no (notumor) for binary classification. The distribution of training and testing datasets for Datatset_MC and Dataset_BC respectively is shown in the following Table 1. Figures 2 and 3 show the different classes of Dataset_MC and Dataset_BC respectively of brain cancer on a different dataset. Dataset_MC is used for multi-classification while Dataset_BC is used for binary classification using the same model.

TABLE I. Distribution of Training and Testing Dataset for Dataset_MC and Dataset_BC

Datasets	Training Dataset	Testing Dataset
Dataset_MC (7023)	5712	1311
Dataset_BC (3000)	2400	600

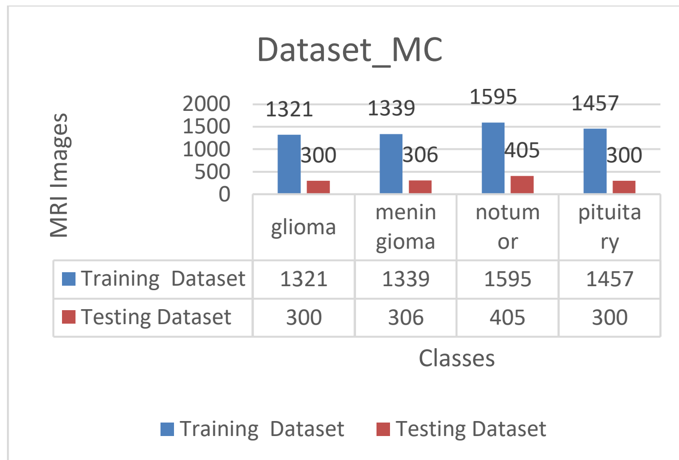

Fig. 2. The different classes of training and testing datasets in Dataset_MC.

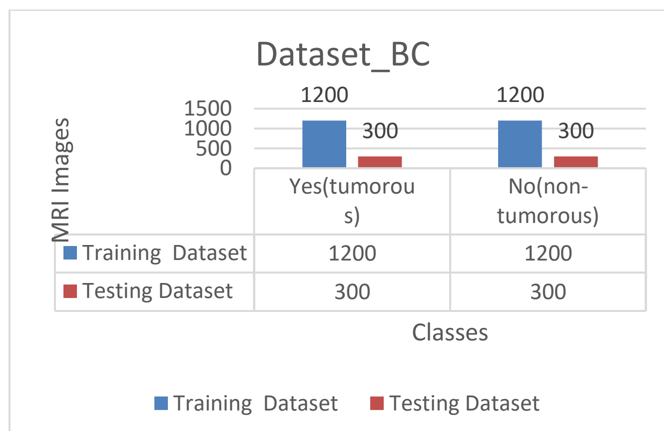

Fig. 3. The different classes of training and testing datasets in Dataset_BC.

VI. Proposed CNN Model

Figure 4 shows a common architecture of the projected model consisting of a few layers with minimum numbers of total parameters for Dataset_MC and Dataset_BC. The difference is only in the last dense layer where the left side uses 4 classes (multi-class) and the right-side uses right side 2 classes (binary-class) in Dataset_MC and Dataset_BC respectively. It is very efficient because of high accuracy and computation time is very less. In the projected hybrid CNN-SVM model, CNN serves as an automatic feature extractor and SVM as a classifier.

Layer (type)	Output Shape	Param #
conv2d_input (InputLayer)	[(None, 48, 48, 3)]	0
conv2d (Conv2D)	(None, 48, 48, 32)	896
batch_normalization (BatchNormalization)	(None, 48, 48, 32)	128
max_pooling2d (MaxPooling2D)	(None, 24, 24, 32)	0
conv2d_1 (Conv2D)	(None, 24, 24, 64)	18496
batch_normalization_1 (BatchNormalization)	(None, 24, 24, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 12, 12, 64)	0
conv2d_2 (Conv2D)	(None, 12, 12, 128)	73856
max_pooling2d_2 (MaxPooling2D)	(None, 6, 6, 128)	0
dropout (Dropout)	(None, 6, 6, 128)	0
flatten (Flatten)	(None, 4608)	0
dense (Dense)	(None, 128)	589952
dense_1 (Dense)	(None, 4)	516

Total params: 684100 (2.61 MB)
Trainable params: 683908 (2.61 MB)
Non-trainable params: 192 (768.00 Byte)

Layer (type)	Output Shape	Param #
conv2d_input (InputLayer)	[(None, 48, 48, 3)]	0
conv2d (Conv2D)	(None, 48, 48, 32)	896
batch_normalization (BatchNormalization)	(None, 48, 48, 32)	128
max_pooling2d (MaxPooling2D)	(None, 24, 24, 32)	0
conv2d_1 (Conv2D)	(None, 24, 24, 64)	18496
batch_normalization_1 (BatchNormalization)	(None, 24, 24, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 12, 12, 64)	0
conv2d_2 (Conv2D)	(None, 12, 12, 128)	73856
max_pooling2d_2 (MaxPooling2D)	(None, 6, 6, 128)	0
dropout (Dropout)	(None, 6, 6, 128)	0
flatten (Flatten)	(None, 4608)	0
dense (Dense)	(None, 128)	589952
dense_1 (Dense)	(None, 2)	258

Total params: 683842 (2.61 MB)
Trainable params: 683650 (2.61 MB)
Non-trainable params: 192 (768.00 Byte)

Fig. 4. Architecture of projected CNN model in Dataset_MC and Dataset_BC.

The proposed deep-learning CNN model uses the following layers to make the robust model:

1) Convolutional layer: It uses a kernel size of 3x3 for feature extraction and is followed by relu function F(x)=Max (0, x). To speed up the training process and convert the negative values to zero.

2) Batch-Normalization layer: It stabilizes the training process and also improves the optimization.

3) Max-polling layer: The 2x2 kernel size of this layer takes the maximum value from the patch of the input data and summarises these values into a features map. By using these it reduces the dimension.

4) Dropout layer: It is set to 0.1 means 10% of neurons drop out in each epoch to reduce over-fitting.

5) Flatten layer: This is the last layer for feature extraction, which converts each batch in the inputs to one dimension.

6) Dense layer: It receives output from every neuron of its preceding layer. In the proposed CNN, two dense layers are used. The first is sigmoid and the second is softmax activation function. The expression of sigmoid function $F(x) = 1/(1+ \ e^{-x})$, which transforms values between the range 0 to 1. The expression of the softmax function is $\sigma(z)_j = e^{z_j}/\sum_{k=1}^{K} e^{z_k} \ \ for\ j = 1,2, \dots . K$

It is like a combination of multiple sigmoid and is used for multi-class classification problems.

VII. Experimental Result and Discussion

The projected CNN model is executed in Jupyter Notebook under Anaconda in Python3 using an Intel Core i5 8th generation laptop.

For ultimate training of the image dataset, the proposed CNN model uses the following hyper-parameters as optimizers: root mean square propagation (RMSprop), learning_rat: 0.0009, and batch_size: 32.

The outcome of the projected CNN model is shown in Figures 5 and 6, which show the accuracy is 100% and 99.2% of the training dataset for Dataset_BC and Dataset_MC respectively in the 10 epochs.

The SVM classifier is applied to feature extraction generated by convolutional layers on the MRI dataset and compares the result through confusion matrix and classification reports. The exhibition of the hybrid CNN-SVM model is better than the standalone CNN architecture. The results show the superiority of the hybrid CNN-SVM in terms of accurateness, and efficiency. The best thing about this proposed model is that rapid and accurate classification of brain cancer can significantly impact treatment planning important to enhanced patient results.

The proposed CNN and hybrid CNN-SVM models were evaluated on the test dataset for Dataset_MC and Dataset_BC. The performance measures of the test dataset are shown by the confusion matrix. The confusion matrix of the projected CNN and hybrid CNN-SVM for Dataset_MC (Upper-Side) and Dataset_BC (Lower-Side) respectively are shown in Figure 7.

```
Epoch 1/10
75/75 [==============================] - 15s 172ms/step - loss: 0.7333 - Accuracy: 0.7146 - val_loss: 0.7100 - val_Accuracy: 0.
5217
Epoch 2/10
75/75 [==============================] - 12s 160ms/step - loss: 0.3619 - Accuracy: 0.8396 - val_loss: 0.8003 - val_Accuracy: 0.
5217
Epoch 3/10
75/75 [==============================] - 12s 160ms/step - loss: 0.1905 - Accuracy: 0.9317 - val_loss: 0.7571 - val_Accuracy: 0.
4850
Epoch 4/10
75/75 [==============================] - 12s 158ms/step - loss: 0.0840 - Accuracy: 0.9742 - val_loss: 0.5120 - val_Accuracy: 0.
7067
Epoch 5/10
75/75 [==============================] - 12s 160ms/step - loss: 0.0474 - Accuracy: 0.9862 - val_loss: 0.3872 - val_Accuracy: 0.
8300
Epoch 6/10
75/75 [==============================] - 12s 160ms/step - loss: 0.0299 - Accuracy: 0.9917 - val_loss: 0.4658 - val_Accuracy: 0.
8217
Epoch 7/10
75/75 [==============================] - 12s 163ms/step - loss: 0.0194 - Accuracy: 0.9942 - val_loss: 0.1555 - val_Accuracy: 0.
9500
Epoch 8/10
75/75 [==============================] - 12s 161ms/step - loss: 0.0124 - Accuracy: 0.9967 - val_loss: 0.0918 - val_Accuracy: 0.
9767
Epoch 9/10
75/75 [==============================] - 12s 158ms/step - loss: 0.0280 - Accuracy: 0.9921 - val_loss: 0.1083 - val_Accuracy: 0.
9750
Epoch 10/10
75/75 [==============================] - 12s 161ms/step - loss: 6.6264e-04 - Accuracy: 1.0000 - val_loss: 0.0911 - val_Accurac
y: 0.9817
```

Fig. 5. The process's result after training in Dataset_BC.

```
Epoch 1/10
179/179 [==============================] - 30s 156ms/step - loss: 0.8220 - Accuracy: 0.7055 - val_loss: 1.6223 - val_Accuracy:
0.4066
Epoch 2/10
179/179 [==============================] - 28s 154ms/step - loss: 0.4065 - Accuracy: 0.8494 - val_loss: 1.0792 - val_Accuracy:
0.5873
Epoch 3/10
179/179 [==============================] - 28s 156ms/step - loss: 0.3005 - Accuracy: 0.8883 - val_loss: 0.6103 - val_Accuracy:
0.7788
Epoch 4/10
179/179 [==============================] - 28s 157ms/step - loss: 0.2204 - Accuracy: 0.9210 - val_loss: 0.3110 - val_Accuracy:
0.8734
Epoch 5/10
179/179 [==============================] - 28s 157ms/step - loss: 0.1574 - Accuracy: 0.9407 - val_loss: 0.3068 - val_Accuracy:
0.8871
Epoch 6/10
179/179 [==============================] - 28s 157ms/step - loss: 0.1087 - Accuracy: 0.9615 - val_loss: 0.1790 - val_Accuracy:
0.9321
Epoch 7/10
179/179 [==============================] - 28s 158ms/step - loss: 0.0828 - Accuracy: 0.9688 - val_loss: 0.1371 - val_Accuracy:
0.9466
Epoch 8/10
179/179 [==============================] - 28s 157ms/step - loss: 0.0462 - Accuracy: 0.9842 - val_loss: 0.4636 - val_Accuracy:
0.8452
Epoch 9/10
179/179 [==============================] - 28s 157ms/step - loss: 0.0400 - Accuracy: 0.9870 - val_loss: 0.1117 - val_Accuracy:
0.9649
Epoch 10/10
179/179 [==============================] - 28s 157ms/step - loss: 0.0266 - Accuracy: 0.9916 - val_loss: 0.1420 - val_Accuracy:
0.9512
```

Fig. 6. The process's result after training in Dataset_MC.

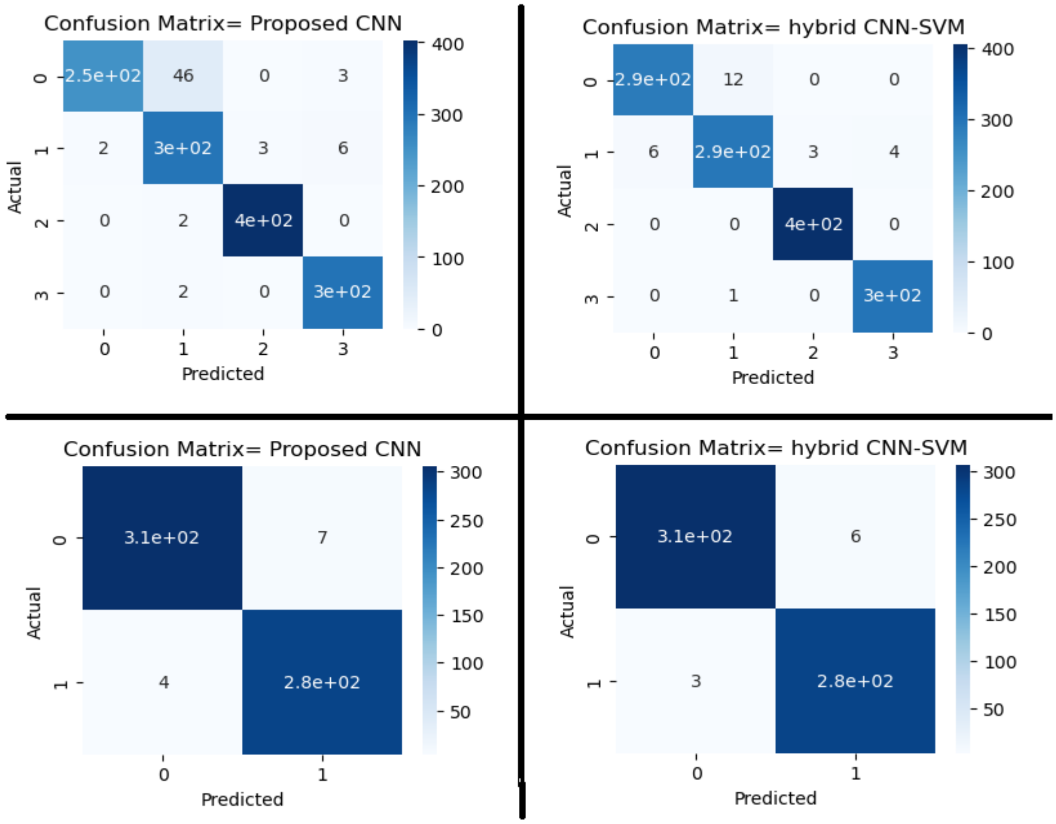

Fig. 7. Confusion matrix for Dataset_MC (Upper-Side) and Dataset_BC (Lower-Side).

TABLE II. CLASSIFICATION REPORT OF TEST DATASET IN DATASET_MC AND DATASET_BC

Test Dataset_MC	Classes	Precision	Recall	F1-score
Proposed CNN Accuracy=95%	glioma	0.99	0.84	0.91
	meningioma	0.86	0.96	0.91
	notumor	0.99	1.00	0.99
	pituitary	0.97	0.99	0.98
Support Vector Machine (SVM) Accuracy=98%	glioma	0.98	0.96	0.97
	meningioma	0.96	0.96	0.96
	notumor	0.99	1.00	1.00
	pituitary	0.99	1.00	0.99
Test Dataset_BC	**Classes**	**Precision**	**Recall**	**F1-score**
Proposed CNN Accuracy=98%	no	0.99	0.98	0.98
	yes	0.98	0.99	0.98
SVM Accuracy=99%	no	0.99	0.98	0.99
	yes	0.98	0.99	0.98

In the addition of the evaluated test dataset, the projected model achieved the best accuracy. Table 2 shows the classification report of all classes of test data in the Dataset_MC and Dataset_BC.

The projected CNN model obtained 95% and 98% accuracy for the test data in the Dataset_MC and Dataset_BC respectively. The best result obtained in the hybrid CNN-SVM model was 98% and 99% accuracy for the test dataset in Dataset_MC and Dataset_BC respectively. It shows high performance not only in training data but also in test data.

Figure 8 shows the accuracy of different classes in the random test images from Dataset_MC (Upper_Side) and Dataset_BC (Lower_Side).

The proposed work is the best as compared to other researchers' work because the same kind of dataset was used by other authors in the experiment but did not get the optimal accuracy, which is shown in Table 3.

Authors [23] proposed a CNN and a hybrid CNN-SVM model for brain cancer binary classification (benign and malignant) and obtained an accuracy of 98.49% using CNN-SVM and 97.43% using CNN on the BRATS 2015 brain image dataset. This is training accuracy, which is less than our proposed work.

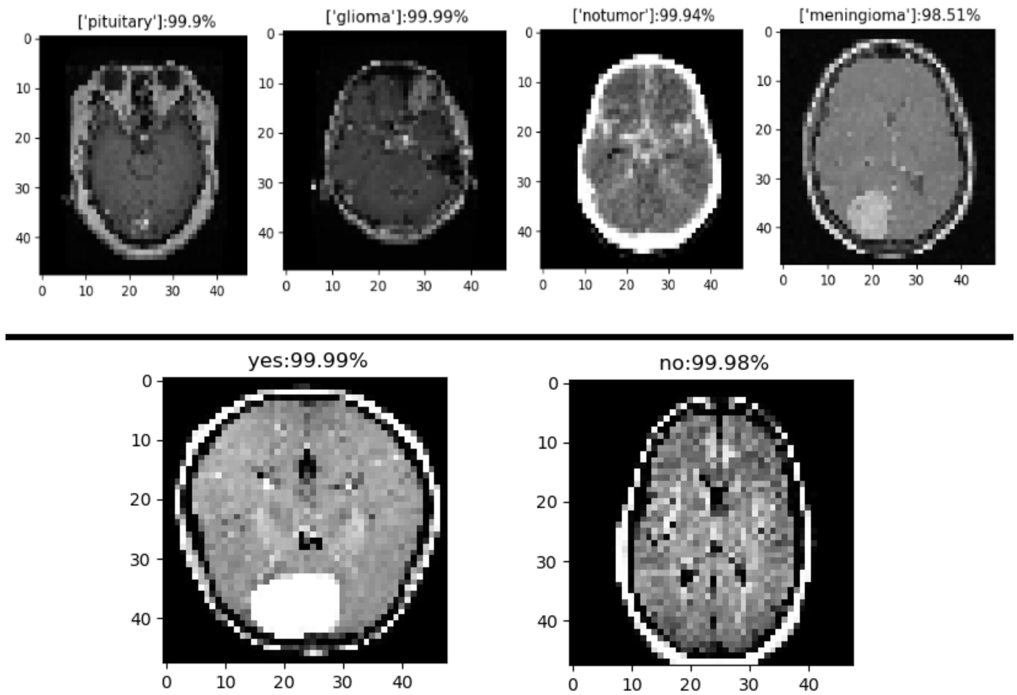

Fig. 8. Sample output of different classes with accuracy from both test datasets.

TABLE III. COMPARISON OF PROJECTED WORK WITH OTHER AUTHOR'S WORK

Reference	Model	Accuracy of the training dataset	Accuracy of the validation/testing dataset	Epoch	MRI Brain Image Dataset
[21]	CNN	85%	88%	10	Dataset_MC
[22]	CNN	94.74%		20	
[24]	CNN	92.66%			
	AlexNet	83.12%			
	VGG-16	88.87%			
[25]	CNN	96.13%			
[26]	CNN-GA	94.2%		100	
	CNN-SVM (Proposed Work)	99.56%	98%	10	
[11]	VGG-19 with AQO	98.95%	98.95%	41	Dataset_BC
[12]	ResNet-50	98%	94%	20	
[13]	VGG-16	96%	86%	10	
[15]	Inception-ResnetV2 with ADSCFGWO	99.98%	-	20	
[24]	CNN	99.33%			
	AlexNet	88.12%			
	ResNet-50	92.79%			
[27]	CNN-SVM	99.74	93.78%	11	
[28]	EfficientNet-B0	98.87%		50	
	CNN-SVM (Proposed work)	100%	99%	10	

Authors [24] projected three CNN models to perform three different tasks on brain tumor MRI image datasets. The first CNN model was used for binary classification (tumor and nontumor) with an accuracy of 99.33%. The second was used to find the multi-class detection (glioma, meningioma, pituitary, metastatic and normal) with an accuracy of 92.66%. In this case, separate models are used by the authors for different tasks while in this paper single model was used for different tasks and accuracy is also higher than the other author’s work.

Authors [26] proposed a CNN-SVM model for brain cancer classification using an MRI dataset and found the accuracy on the training dataset is 99.74% using RMSProp optimiser in 11 epochs but testing accuracy is 93.78%, which is much less as compared to our proposed work.

VIII. Conclusion and Future Discussion

Each type of problem has a specific CNN model created for it. The kind of problem, the inputs, and the anticipated results all affect the CNN model's architecture and complication. The maximum authors were used to propose different classification models for the diverse classification tasks. Selecting the best-performing network model for a given application is one of the challenges with convolutional neural networks. Making the correct hyper-parameter choices is critical to accomplishment best outcomes, especially with the CNNs.

The most effective CNN model is created in this study, and its hyper-parameters are optimized and large, freely accessible MRI datasets are used to achieve satisfactory categorization results. Using the projected CNN model on test datasets, brain cancer identification is accomplished with a very pleasing accuracy of 99% for binary classification. Furthermore, a 98% accuracy rate is achieved for multi-classification. Finally, using performance evaluation criteria including accuracy, precision, recall and F1 score, the outcome of the proposed CNN-SVM is verified.

The one limitation of this study is that the accuracy of test data can be increased if the size of datasets is increased since it takes more time to improve the data by the augmentation process, which does not impact the result.

Future research in healthcare applications will continue to focus heavily on deep learning. The proposed model can be generalised based on its capacity to categorize data, it can be utilized to recognize and diagnose medical conditions. Because medical training takes a long time, this not only shortens the diagnosing process but also decreases the number of mistakes made by professionals. This concept holds promise for medical imaging diagnostics since combining data from several sources can result in a distinct course of events. Additionally, putting the system for crowdsourcing data collecting and analysis into practice will be interesting. Lastly, there are numerous healthcare sectors where deep learning can be applied.

MRI remains at the forefront of non-invasive brain cancer detection offering clinicians a comprehensive view of cancer morphology and aiding in treatment decision-making. The integration of CNN and MRI can alter the scene of diagnostic tools for brain tumors, providing clinicians with more reliable and timely information for patient care.

The future of MRI-based brain cancer detection holds promise with ongoing research in imaging expertise and artificial intelligence. Continuous progresses in imagery technology and the integration of DL will continue to improve the correctness and consistency of MRI in tumor characterization.

Declaration

- Availability of supporting data: The datasets are available on the following link: https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset. https://www.kaggle.com/datasets/ahmedhamada0/brain-tumor-detection.
- Competing Interests: No conflicts of interest
- Authors’ Contributions: Everyone contributed to the research methodology and analysis of results.
- Funding: No source of funding.
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