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COMPUTER-AIDED DIAGNOSIS AND DETECTION FOR PATIENT'S BRAIN CANCER

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Abstract

The most severe form of cancer sickness is brain tumor. It arises from uncontrollable and strange cell division. Brain tumors can be classified into benign and malignant tumors. The recognition of brain tumors is a complex mission that implied the experience of the classifier. The manual classification of tumor types using data gathered from MRIs is believed to be an exhausting task that may result in human error and false tumor type detection.
In this paper, we compared ML and DL different algorithms for brain tumor classification such as VGG-16, CNNs, SVM, and KNN to categorize four types of brain tumors (meningioma tumor(originate in the meninges), glioma tumor(improve from different types of glial cells), pituitary tumor (non-threatening tumor), and no tumor.DL achieved high results with accuracy 99% for CNN and 90% for VGG16 (not just accuracy was used for estimating these models, other evaluation metrics will be calculated as discussed later) , while ML didn't achieve suitable results for brain tumor classification, SVM achieved 91% accuracy .This experimental study was implemented on a real time dataset with different tumor sizes, locations, shapes, and different image intensities.

Keywords

Brain Tumor; Cell Division; Malignant Tumor; Tumor Sizes; Image Intensities.

1. Introduction

The brain is an important organ in the human body. It controls all processes in the body, so it is necessary to keep brain healthy. A lump or collection of aberrant brain cells is known as "a brain tumor." Tumor is an uncharacteristic growth of cells in or out of human body. It coexists when a cell does not grow well or dies. This tumor can disturb the brain's natural behavior and produce rise in stress in it. So, some tissues may be pushed against the brain, resulting in destroying the healthy brain tissues. Tumors can be classified according to many features, such as the position where they arise and the kind of cell. Any expansion inside such a constrained area can lead to significant issues. Brain tumors divided into two categories non-cancerous (benign), which requires treatment before spreading to other areas of the original organ, or cancerous (malignant), which may recur following therapies. Malignant or benign tumors that have spread may have an impact on the pressure inside the skull. This has the potential to be fatal and can result in brain damage. For the diagnosis and identification of brain tumors, more current imaging technology has shown great effectiveness in the field of medical imaging. The more beneficial imaging techniques for brain cancers include MRI (Magnetic Resonance Imaging) and CT (Computed Tomography) scans.

In contrast to CT images, MRI scans are more helpful since they provide information on the texture and shape of the tumor. It is simple to compute the size, shape, and position of the detective tissues using MRI. These methods also have a few drawbacks, such as a high computational cost.

The manual classification of tumor types using data gathered from MRIs is believed to be an exhausting task that may result in human error and false tumor type detection.

A computer-aided diagnosis (CAD) system may be beneficial for a radiologists' second opinion in clinics for the early detection and classification of brain tumors.

2. Literature Review

In brain tumor detection, they have studied feature-based existing work (Ankita, 2020) [1]. They have conducted numerous studies in features-based image processing on methods for processing images, including image pre-processing, picture segmentation, extraction of features, and classification. Studies on deep learning methods such as CNN and VGG16 were also conducted. The dataset they used has 556 images with different types of tumors and also includes images that have tissues of fat or water. They have compared CNN with the VGG 16 model. The result of the comparison, VGG 16 (85.54%), is more accurate than CNN (72.699%).

An operative brain cancer categorization method that has three central stages was introduced (Gumaei *et al*., 2019) [2].In the beginning, a preprocessing procedure is used to convert intensity values from brain images. A new and effective hybrid technique called PCA-NGIST is then used to extract the most crucial features. The RLEM classifier is then employed to categorize brain tumors. Using a fresh dataset of available brain tumor images, the classification performance of the suggested approach is assessed and contrasted. This dataset includes 233 patients' 3064 brain scans, each of which shows three different forms of brain tumors. Fivefold cross-validation and holdout (70% training, 30% testing) approaches are used in these investigations. The experimental findings supported the claim that the suggested PCA-NGIST feature extraction approach provides greater accuracy than PCA-GIST, GIST, or NGIST methods. Moreover, the obtained results indicated that the suggested approach reached high sorting rates compared with the state-of-the-art.

The MR image's cropping decreases the number of pixels for training, rising the rate of training while providing competitive segmentation outcomes (Lagergren & Rosengren, 2020) [3]. When trained end-to-end, the unique multi-stream U-Net design outperformed the traditional method. Segmentation's variance is reduced when deep learning is used. In order to better understand tumor progression, a more accurate calculation of the tumor size can be made. The training of the single-stream U-Net is compared across two distinct types of network designs and the effects of various regularization methods. Furthermore, it examines how performance is impacted by two distinct methods of training the multi-stream U-Net. Performance is better in the multi-stream U-Net trained end-to-end. Not all of the single-stream U-Net studies showed improved performance when the regularization strategies were added on top of one another. Occasionally, there aren't many performance differences between different regularization methods. When comparing performance differences after adding L2 regularization, the accuracy fell by 0.5%. The stochastic characteristics of the ANN may have contributed to this decline. The network might have done better if the L2 regularization algorithm hadn't been used. Repeating the experiment more than once would have improved the accuracy and repeatability of our findings.

In our proposed model we proved that deep learning achieved the best results for brain tumor classification using CNN.We achieved accuracy 99.5 % with our proposed model.

3. Research Methodology

Because of suitable database used in this paper, we chose to implement both of DL (using CNN & VGG16)and ML (using SVM &KNN)and compare between their performances.

3.1 Description of Database

Our dataset is a combination of two datasets used in kaggle

- (Brain Tumor Classification (MRI) dataset)(Bhuvaji, 2020) [4] ,contains 2870 training images (826 glioma tumor, 822 meningioma tumor, 395 no-tumor, 827 pituitary tumor) and 394 testing images (100 glioma tumor, 115 meningioma tumor, 105 no-tumor, 74 pituitry tumor)
- (Brain Tumor MRI Dataset)(Nickparvar, 2021) [5], contains 5712 training images (1321 glioma tumor, 1339 meningioma tumor, 1595 no-tumor, 1457 pituitary tumor) and 1311 testing images (300 glioma tumor,306 meningioma tumor, 405 no-tumor, 300 pituitary tumor).The dataset we used was combined as shown in Table1.

Table 1. Dataset Used in our Problems.

Brain tumor	training image	testing image
Glioma tumor {Tumor_1}	2147	400
Meningioma tumor {Tumor_2}	2161	421
Pituitary tumor{Tumor_3}	2284	374
No-tumor {Tumor_4}	1990	510
Total	8582	1705

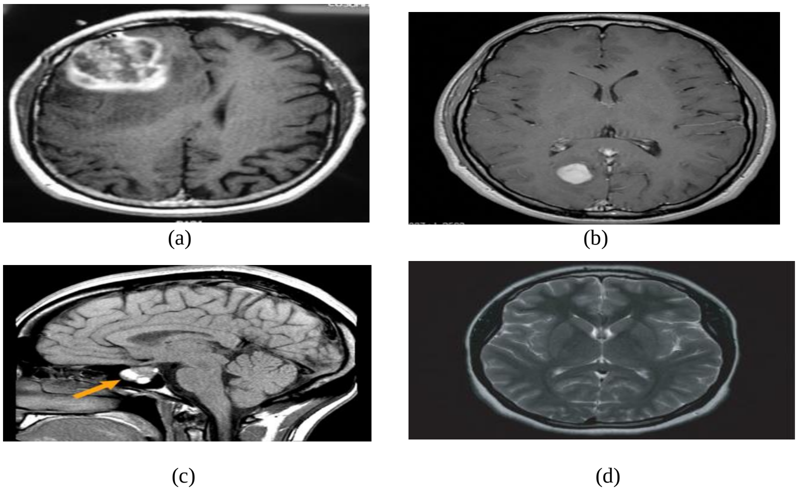

Figure 1. Different Types of Brain Tumor (a) Glioma Tumor [6], (b) Meningioma Tumor[7], (c) Pituitary Tumor[8], (d) No-Tumor[9] .

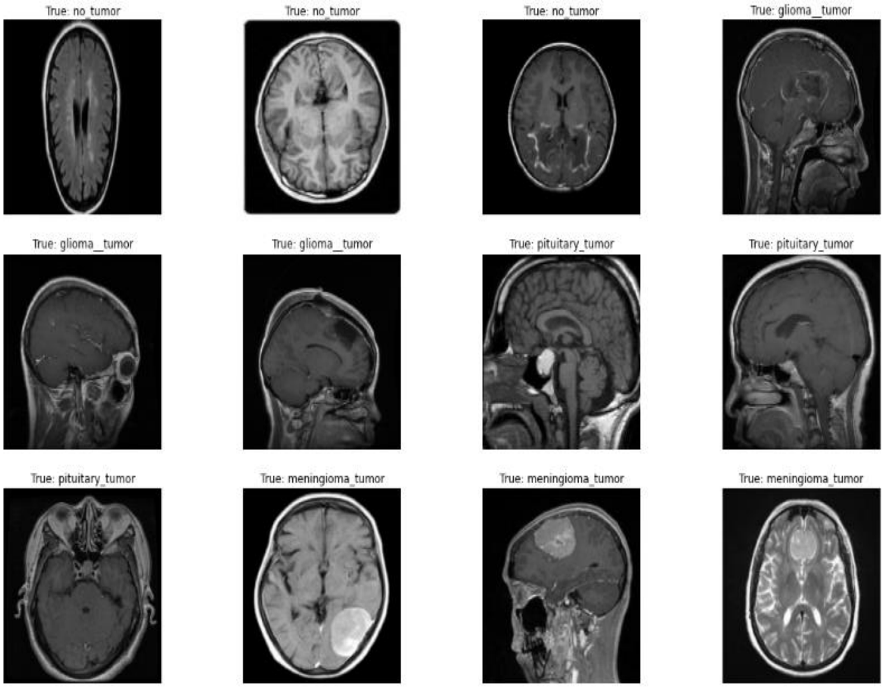

Figure 2. Some Images Used for Training Proposed Models[10].

3.2 CNN implementation

In this paper we implement five different models of CNN with different changeable parameters as declare in Table 2.

Table 2. CNN Models.

CNN model	Layer count	Learning rate	epochs	Input image size
1	3	0.001	60	150×150
2	3	0.001	50	512×512
3	2	0.001	100	128×128
4	4	0.001	100	128×128
5	3	0.001	100	128×128
6	9	0.001	100	224×224

Small learning rates were adjusted in order to not distort CNN very quickly. we configure our CNN model with Adam optimizer [10] .In the last model we used data augmentation to inrease number of training image.we change input image size , we apply 9 layers in that model trying to achieve best result .

3.3 VGG16 implementation

We Preprocessed data with size (150, 150).We loaded p retrained convolutional layers using Image Net weights. We merge the data and augment the training data with (fill mode = nearest, shear range = 0.2, zoom range = 0.2, horizontal flip = true, and validation split = 10%). We set epoch to 60, and learning rate=0.001.

3.4 SVM implementation

We applied polynomial SVM, and adjust the hyper parameters of it, the degree of the polynomial function (d), and the regularization parameter (C) to get the best result. We applied it to training data to be able to predict our testing images.

3.5 KNN implementation

We apply our KNN model to predict testing image by using Euclidean distance to find the nearest neighbor.

4. Reduce over fitting

To reduce over fitting we used callbacks (model check point, reduce LR0n plateau, and early stopping) for monitoring validation loss with minimum value.

5. Models evaluation

To evaluate the effectiveness of a machine learning classification task where the output can be two or more classes, a confusion matrix was created.

For measuring recall, precision, specificity, and accuracy, it is incredibly helpful.

Allow me to explain TP, FP, FN, and TN.

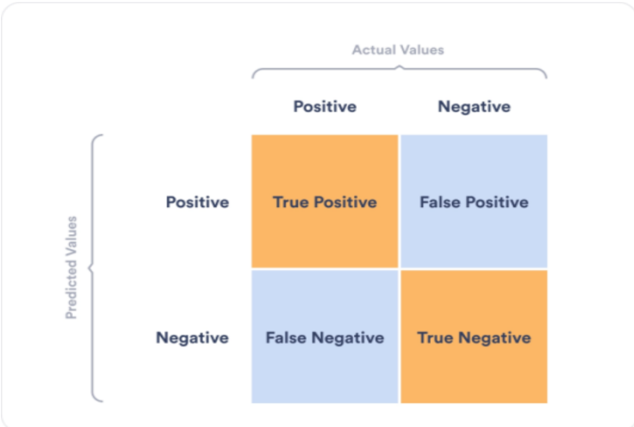

Figure 3. Confusion Matrix [11]

- **True Positives:** When our optimistic predictions came true and the result was also positive,
- **True Negatives:** Situations in which we expected a negative result and it actually appeared as a negative
- **False Positives:** Situations in which we anticipated a positive result but got a negative one instead
- **False Negatives:** These are instances where we expected a negative result but got a positive result instead.

We calculate accuracy, precision, F1-score and recall according to the following Equation s(12).

$$\text{Accuracy} = \frac{(\text{TP+TN})}{\text{total samples}} \qquad (12)$$

$$\text{F1 Score} = 2^* \frac{1}{\left(\frac{1}{\text{precision}}\right)+\left(\frac{1}{\text{recall}}\right)} \qquad (12)$$

$$\text{Precision} = \frac{TP}{TP+FP} \qquad (12)$$

$$\text{Recall}= \frac{TP}{TP+FN} \qquad (12)$$

6. Results discussion

We obtained the following results of accuracy and loss graphs for our proposed models. Every model showed different performance in both of training and testing process. The models made early stopping at different epochs to avoid over fitting .we also get confusion matrix for every model, for easily comparing between them.

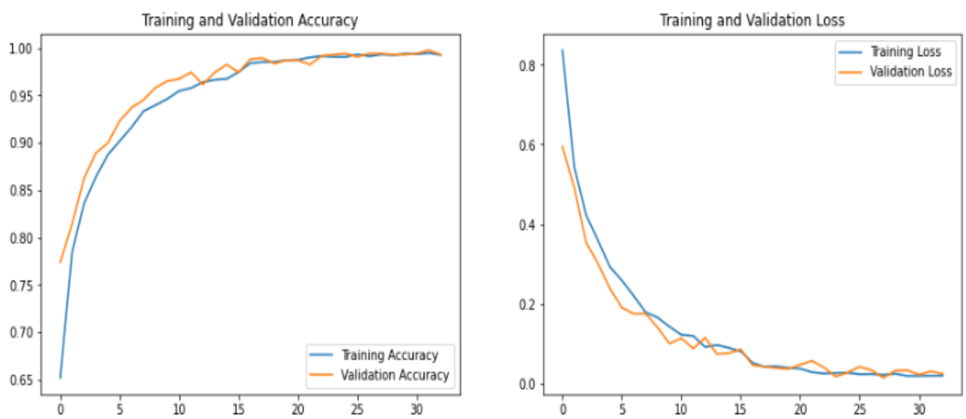

Figure 4. Accuracy and Loss graphs for CNN model 1.

```
Evaluate on test data
54/54 [==============================] - 1s 9ms/step - loss: 1.2340 - accuracy: 0.9331
test loss: 1.23, test acc: 0.93
```

Figure 5. Accuracy and Loss values for testing images for CNN model 1.

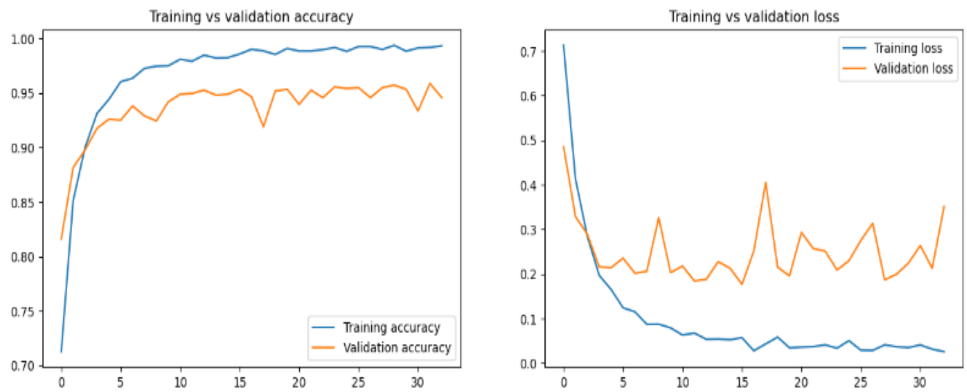

Figure 6. Accuracy and Loss graphs for CNN model 2.

```
386/386 [==============================] - 11s 29ms/step - loss: 0.4191 - accuracy: 0.9501

Out[22]:
0.950129508972168
```

Figure 7. Accuracy and Loss values for testing images for CNN model 2.

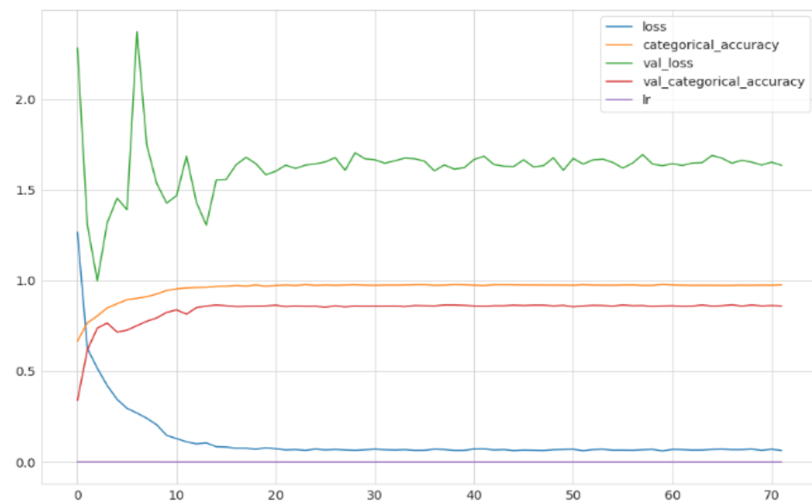

Figure 8. Accuracy and Loss graphs for CNN model 3.

```
22/22 [==============================] - 3s 133ms/step - loss: 0.1430 - categorical_accura
cy: 0.9633

[0.1429525464773178, 0.9632892608642578]
```

Figure 9. Accuracy and Loss values for testing images for CNN model 3

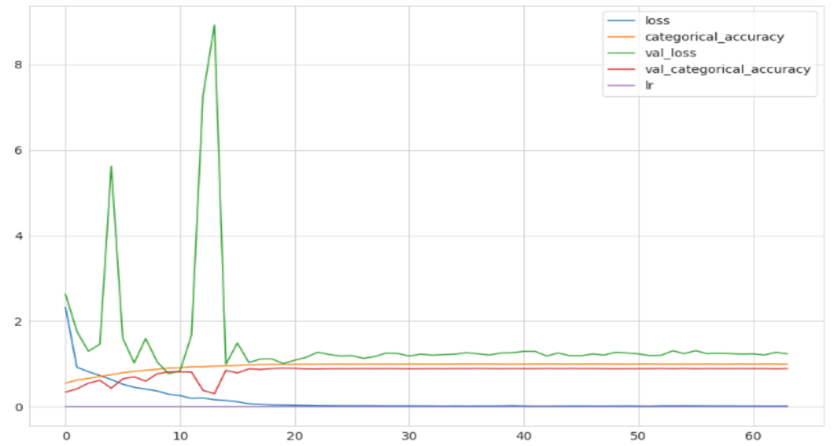

Figure 10. Accuracy and Loss graphs for CNN model 4.

```
22/22 [==============================] - 4s 154ms/step - loss: 0.0228 - categorical_accura
cy: 0.9941

[0.022831520065665245, 0.9941262602806091]
```

Figure 11. Accuracy and Loss values for testing images for CNN model4.

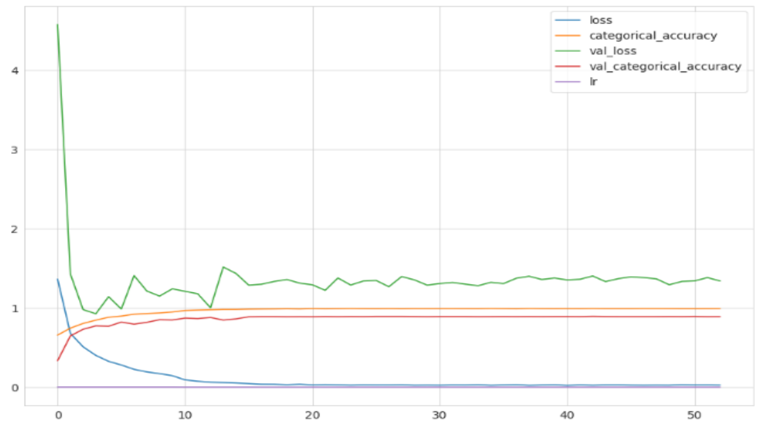

Figure 12 . Accuracy and Loss graphs for CNN model 5.

```
22/22 [==============================] - 3s 138ms/step - loss: 0.0395 - categorical_accura
cy: 0.9941

[0.039542652666568756, 0.9941262602806091]
```

Figure 13. Accuracy and Loss values for testing images for CNN model 5.

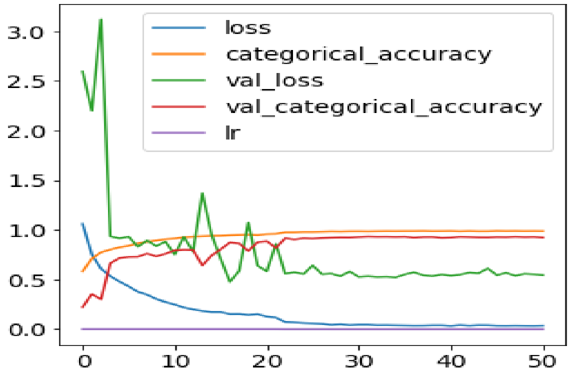

Figure 14 . Accuracy and Loss graphs for CNN model 6

```
14/14 [==============================] - 1s 94ms/step - loss: 0.0260 - categorical_accurac
y: 0.9953

[0.026010500267148018, 0.9952940940856934]
```

.

Figure 15 . Accuracy and Loss values for testing images for CNN model 6.

Figure16 . Accuracy and Loss graphs for VGG16 model.

```
54/54 [==============================] - 3s 46ms/step - loss: 0.6504 - accuracy: 0.9021
```

Figure 17 . Accuracy and Loss values for testing images for VGG16 model.

Table 3. F1_Score and Accuracy Results for Different Degrees and Regularization Parameters for Polynomial SVM.

	d=2				d=3			
C	0.1	1	10	100	0.1	1	10	100
F1-score	71.57	87.36	91	90.88	77.69	90.03	91.01	91.17
accuracy	71.79	87.51	91.2	91.09	77.65	90.15	91.2	91.38

Table 4 . F1_Score and Accuracy Values for KNN Model.

K	1	2	5	8	10	12	15	19	20
F1-score	92.9	91.4	82.3	77.6	73.8	72.1	67.9	65.4	65.2
accuracy	93.1	92.3	85.35	78.7	74.1	73	69	67.32	66

Table 5 .Confusion Matrix for CNN Model 1.

True labels	Predicted labels				Sensitivity (Recall)
	Tumor _1	Tumor _2	Tumor _3	Tumor _4	
Tumor _1	314	35	1	50	0.78
Tumor _2	1	415	1	4	0.99
Tumor _3	0	10	352	12	0.94
Tumor _4	0	0	0	510	1
Precision	1	0.99	0.9	0.89	Total accuracy= 0.93

Table 6 .Confusion Matrix for CNN Model 2.

True labels	Predicted labels				Sensitivity (Recall)
	Tumor _1	Tumor _2	Tumor _3	Tumor _4	
Tumor _1	339	22	6	5	0.92
Tumor _2	19	357	10	1	1
Tumor _3	2	0	415	0	0.91
Tumor _4	3	1	3	361	0.98
Precision	0.94	0.96	0.93	0.98	Total accuracy= 0.95

Table 7 .Confusion Matrix for CNN Model 3.

True labels	Predicted labels				Sensitivity (Recall)
	Tumor _1	Tumor _2	Tumor _3	Tumor _4	
Tumor _1	159	1	0	0	0.99
Tumor _2	0	145	1	22	0.89
Tumor _3	0	0	148	1	0.99
Tumor _4	0	0	0	204	1
Precision	1	0.99	0.99	0.9	Total accuracy= 0.96

Table 8 .Confusion Matrix for CNN Model 4.

True labels	Predicted labels				Sensitivity (Recall)
	Tumor _1	Tumor _2	Tumor _3	Tumor _4	
Tumor _1	160	0	0	0	1
Tumor _2	0	165	1	2	0.98
Tumor _3	0	0	149	0	1
Tumor _4	0	0	0	204	1
Precision	1	1	0.99	0.99	Total accuracy= 0.99

Table 9 .Confusion Matrix for CNN Model 5.

True labels	Predicted labels				Sensitivity (Recall)
	Tumor _1	Tumor _2	Tumor _3	Tumor _4	
Tumor _1	160	0	0	0	1
Tumor _2	1	163	1	3	0.97
Tumor _3	0	0	149	0	1
Tumor _4	0	0	0	204	1
Precision	0.99	1	0.99	0.99	Total accuracy= 0.99

Table 10 .Confusion Matrix for CNN Model 6.

True labels	Predicted labels				Sensitivity (Recall)
	Tumor _1	Tumor _2	Tumor _3	Tumor _4	
Tumor _1	99	0	0	1	0.99
Tumor _2	0	104	1	0	0.99
Tumor _3	0	0	93	0	1
Tumor _4	0	0	0	127	1
Precision	1	1	0.99	0.99	Total accuracy= 0.995

Table 11 .Confusion Matrix for VGG16 Model .

True labels	Predicted labels				Sensitivity (Recall)
	Tumor _1	Tumor _2	Tumor _3	Tumor _4	
Tumor _1	284	72	9	35	0.71
Tumor _2	4	387	21	9	0.92
Tumor _3	0	10	367	7	0.95
Tumor _4	0	0	0	510	1
Precision	0.99	0.83	0.92	0.91	Total accuracy= 0.90

Table 12 .Confusion Matrix for SVM Model.

True labels	Predicted labels				Sensitivity (Recall)
	Tumor _1	Tumor _2	Tumor _3	Tumor _4	
Tumor _1	308	24	26	42	0.77
Tumor _2	22	387	4	8	0.92
Tumor _3	3	15	354	2	0.95
Tumor _4	1	0	0	509	1
Precision	0.92	0.91	0.92	0.91	Total accuracy= 0.91

7. Analysis

At the end we introduce the metric evaluation for these models in Table 13.

Table 13 .Metric Evaluation for Proposed DL&ML Algorithms

Models implemented	CNN models						VGG16	SVM	KNN
	1	2	3	4	5	6			
Accuracy (%)	93	95	96	99	99	99.5	90	91	68
Precision (%)	94	95	98	99	99	1	91	91	70
F1-score (%)	93	95	97	99	99	1	90	91	65

We compared all algorithms we used. ML algorithms didn't show acceptable performance for medical images training. CNN shows good performance for medical images training .We can increase this performance by Training more images, increase epochs, and decrease the learning rate. We can decrease time processing with GPU.

We can compare our proposed model with previous studies with different authors using different algorithms.

Table 14 .Comparing different algorithms used for detecting brain tumor.

citation	author	year	algorithm	accuracy
[1]	Ankita	2020	CNN	72.7
			VGG16	85.54
[2]	Abdu Gumael &Mohammed Mehedi	2019	SVM	91.51
			NBNaive	84.33
			PCA-NGIST With RELM	94.233
[3]	Linus Lagergren &carl Rosengren	2020	Multi-stream UNet	97

8. Conclusion

In this paper, using deep learning and machine learning methods, we attempted to categorize MRI data sets of brain tumors. The purpose of the experiment is to evaluate how well CNN, VGG16, SVM, and KNN process brain tumor classification issues. Python 3.7 is employed as the development language for our projects. Build our SVM and KNN models using the Sklearn library, and our CNN and VGG16 models using the Keras library. Separately, we examined each model's parameters, including the terminology and procedure of C and the selection of the kernel function in SVM. We also use Euclidean distance to find the nearest neighbor for KNN. At the same time, we also introduces the parameter selection of convolutional layer, pooling layer and fully connected layer for CNN and VGG16.we studied the performance of each model separately, Finally we compared all results together. CNN show high accuracy 99% with high running time, in contrast to the VGG16 that gave 91% accuracy with appropriate running time. SVM and KNN show poor performance for brain image training

9. Future work

Many suggestions can be taken in consideration to present accurate model for detecting brain tumor in the future.

- We have to increase data set used for detecting tumors.
- We can try more classifiers to increase the accuracy.
- We have found a suitable preprocessing system for brain tumor MRI categorization.

We need to take running time in consideration; such a serious disease may not allow a lot of time to be detected.

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التشخيص والكشف بمساعدة الكمبيوتر لمرضى سرطان المخ

الخلاصة

تعد اورام الدماغ من أخطر أنواع السرطانات. وهي تحدث عن طريق أجزاء من الخلايا غير طبيعية ويصعب التحكم بها. أورام الدماغ من الممكن تصنيفها إلى أورام سرطانيه وأورام غير سرطانية. يعتبر تشخيص أورام الدماغ مهمة معقده، والتي تتضمن خبرة المصنف. ويعد الاكتشاف غير المعتمد على الحاسب للمرض من خلال صورة الرنين المغناطيسي هو مضيعه للوقت ومن الممكن أن يؤدى إلى أخطاء بشرية وأيضا يؤدي إلى التشخيص والتصنيف الخاطئ لنوع الورم. في هذه الرسالة قمنا بمقارنة خوارزميات تعلم الآلة والتعلم العميق لاكتشاف وتصنيف أورام الدماغ باستخدام الشبكة العصبية الالتفافية والآلات ناقلات الدعم وأقرب جار، لتصنيف أربعة أنواع من الأورام وهى: الورم السحائي، ورم الغده النخامية، الورم الدبقي، ولا يوجد ورم. ولقد حقق التعلم العميق نتائج عالية الدقة لتصنيف هذه الأورام، حيث كانت دقة الشبكة العصبية 99% (ليست الدقة فقط هي المعيار الوحيد المستخدم في تقييم تلك الطرق، لكن هناك أيضا تقييمات أخرى تم حسابها كما هو موضح). وعلى النقيض لم يحقق تعلم الآلة النتيجة المرجوة لهذا التصنيف. حيث كانت دقة الآلات ناقلات الدعم 91%. تم دراسة هذه التجارب على قاعدة بيانات فعلية ذات أحجام مختلفة للورم ومواقع وأشكال وحدة عرض مختلفة للصور.

كلمات مفتاحيه: أورام الدماغ، انقسام الخلية، الورم الدبقي، حجم الورم، حدة عرض الصور.