Investigation of VGG-16, ResNet-50 and AlexNet Performance for Brain Tumor Detection

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Abstract—Malignant brain tumours are extremely frequent and deadly, and if they are not found in their early stages, they can shorten a person's lifespan. After the tumour has been detected, it is essential to classify the tumour in order to develop a successful treatment strategy. This study aims to investigate the three deep learning tools, VGG-16 ResNet50 and AlexNet in order to detect brain tumor using MRI images. The results performance are then evaluated and compared using accuracy, precision and recall criteria. The dataset used contained 155 MRI images which are images with tumors, and 98 of them are non-tumors. The AlexNet model perform extremely well on the dataset with 96.10% accuracy, while VGG-16 achieved 94.16% and ResNet-50 achieved 91.56%. The early diagnosis of cancers before they develop physical side effects like paralysis and other problems is positively impacted by these accuracy.

Keywords—brain tumor, classification, Vgg-16, Reset-50, AlexNet

1 Introduction

Brain tumors [1, 2] are the result of aberrant tissue growth within the human skull. They might be benign or cancerous. Additionally, it may be divided into primary brain tumors and secondary cancers that develop in other organs. There are other types of medical imaging procedures, such MRI scans [3, 4] and computed tomography (CT), can be utilized to depict what is occurring within the brain. These photos depict various shapes and sizes of tumors. The difference between a tumor and surrounding tissue regions relies on the tumor's intensity and nature. The challenge of automatic tumor detection necessitates using intelligent algorithms based on image processing tools to distinguish between tumor and normal regions in brain pictures with varying modalities.

To identify brain MRI pictures, current framework systems use a variety of pre-established processes [2–4]. Prakash [1] discuss the efficient methods involved in identifying and classifying tumour units in MRI brain imaging. MRI brain scans are the most common images used as input [3]. The input could be 2D or 3D depending on the architecture and memory constraints. The input regarding the photographs to be submitted has shown to be as vital as any other stage because of its effectiveness in greatly boosting image data [4–6].

Machine learning is a broad phrase, and deep learning is a subset of it. This research intends to create a system that employs computer-based methods to identify brain cancers and categorise the kind of tumour present in MRI images [5, 6] of a range of patients utilizing the Convolution Neural Network Algorithm. image segmentation, image enhancement, and feature extraction are just a few of the image processing methods utilised in locating brain tumors in cancer patients' MRI scans. Image Preprocessing, Image Segmentation, Feature Extraction, and Classification are the four processes in utilizing image processing techniques to detect a brain tumor. Classification is the final step in the process by utilizing image processing and neural networks results in an improvement in both the ability to locate and categorize brain tumors in MR images [6, 7].

It should be noted that VGG-16 [8], ResNet-50 [9], and AlexNet [10] have been extensively utilised as benchmark models for numerous computer vision tasks, including object recognition and picture classification, and have been demonstrated to perform well on many datasets. These models are frequently employed as baseline models to achieve high accuracy on various medical image analysis, including the categorization of brain tumours.

The deep neural network VGG-16, which was first suggested in 2014, has been demonstrated to perform at the cutting edge on image categorization tasks. ResNet-50, which was developed in 2015, pioneered the idea of residual connections and made it possible to train incredibly deep neural networks. However, AlexNet was the first deep learning architecture to show that deep neural networks might be used for computer vision problems.. It consisted of five convolutional layers and three fully connected layers.

These 3 models, despite being based on classic designs, are nevertheless useful today since they offer a solid foundation for comparison with more modern and sophisticated structures. These architectures are frequently used by researchers as a springboard for creating fresh architectures or enhancing current ones. Also, a lot of pre-trained models are available for these architectures, making it simple for developers to employ them in their applications. These architectures are also frequently used in industry and academics. Overall, there is sufficient study and data to justify the use of the baseline models VGG-16, ResNet-50, and AlexNet for the categorization of brain tumours using MRI scans.

2 Methodology

2.1 Overview proposed system

Feature extraction from the dataset serves as the foundation of the architecture. Before dividing the retrieved images into a training set and a testing set, preprocessing is required. Preprocessing, data augmentation, and classification are all done during the training phase to create a prediction model. Finally, the suggested architectures of the VGG-16 [8], ResNet-50, and AlexNet are applied to the used datasets. The block diagram of the proposed system is presented in detail in Figure 1 [11, 12].

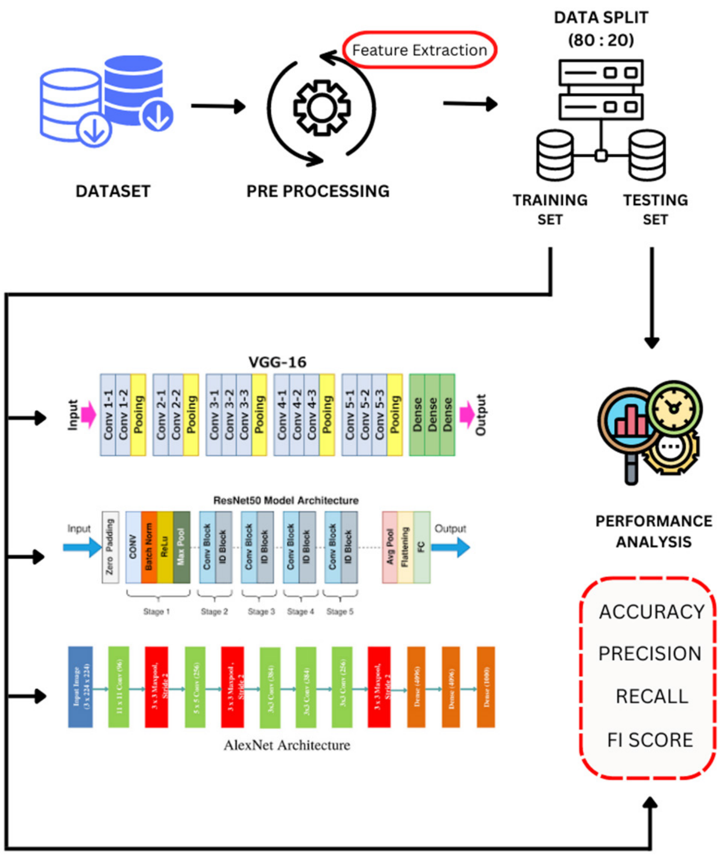


Fig. 1. General overview of proposed system

2.2 Flowchart

In this study, a convolution neural network is used to efficiently identify brain tumours automatically. Python is used to do out simulations. The protocol for detecting a brain tumour is shown in Figure 2.

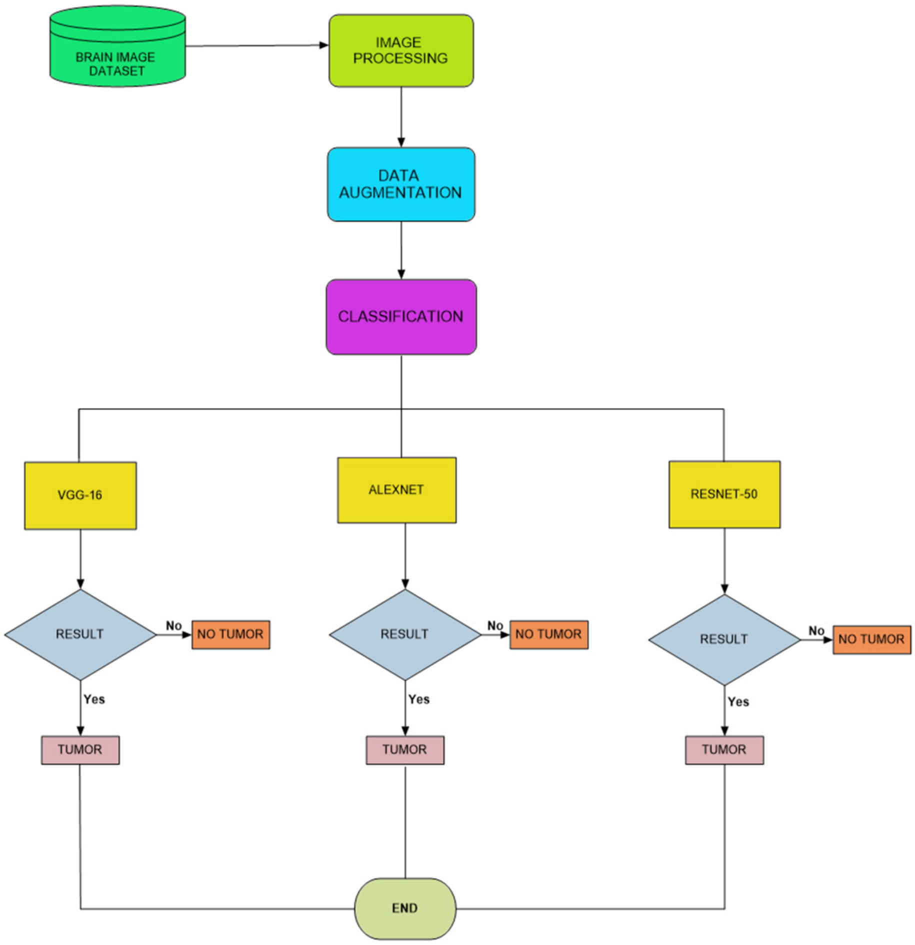
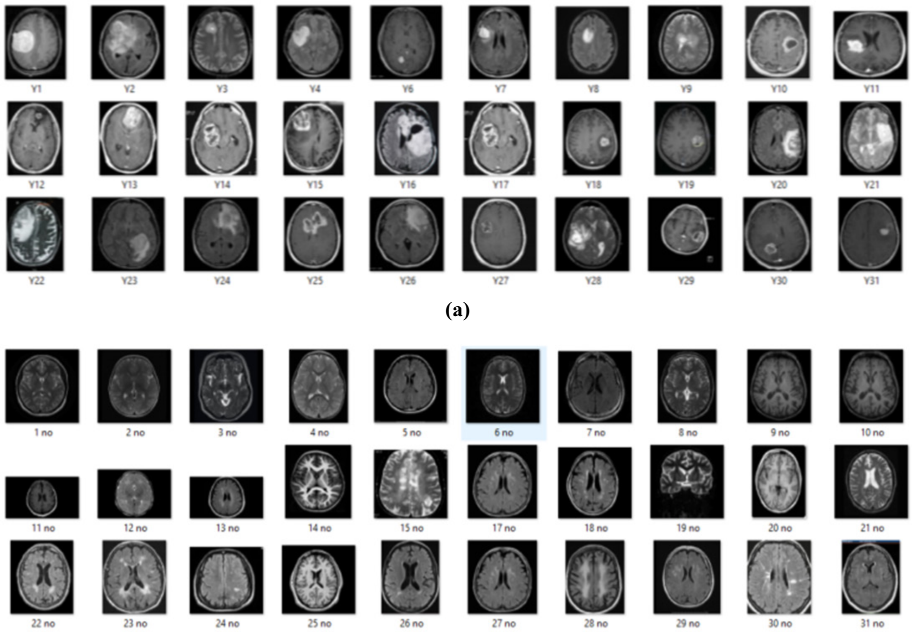


Fig. 2. Flowchart of the project

2.3 Dataset

The study's data set was obtained from Kaggle [13]. There are 253 images in the brain tumour MRI data collection. These photos are separated into the yes and no categories. There are 155 images in the yes category that show brain scans with tumours, and there are around 98 images in the no folder that show brain images without tumours, or what is known as normal. The Kaggle website offers a download for this publicly available dataset. The dataset of MRI brain images with and without tumor are shown as in Figure 3a and b, respectively.



(a)

(b)

Fig. 3. Dataset of MRI image, (a) with tumor, and (b) with no tumor

2.4 Computing platform

In this study, Google Colaboratory, which is built on the Jupyter notebook, was used for all of the training trials. This notebook provides straightforward libraries, visualisation, and data integration tools. It is free software that allows you to run and share Python programmes. The purpose of this platform is to promote machine learning research and teaching [14]. This platform can run on high-performance hardware such Parallel Tensor Processing Units (TPUs) and Graphic Processing Units, with quick training lasting up to 12 hours per user every session (GPUs). In this research, the TensorFlow API, which supports deep neural network architectures, was used to build the VGG16, ResNet-50, and AlexNet models.

2.5 Evaluation parameters

Deep learning architectures were used for brain tumor image classification. There are certain criteria that express the performance of models in deep learning. All of these performance metrics were calculated using the Confusion Matrix. The PC used in the present work has an Intel(R) Core (TM) i5-6200U CPU, 2.30 GHz processor, 4 GB RAM and a 1 TB hard disk. This evaluation is based on how accurately the model classifies the sample in the test set. The confusion matrix for the calculation of accuracy, precision, recall, and F1 defines the words TP, TN, FP, and FN from the expected outcome and ground truth result.

3 Result and discussion

3.1 Setup hyperparameters

In this project, the techniques for evaluating the model results precision, recall, accuracy, and F1 score are addressed. With Kaggle, sequential models based on the VGG-16, ResNet-50, and AlexNet were developed. Table 1 lists the hyperparameters that were applied to each model. A convolutional neural network model implements the transfer learning strategy. The Google Colab environment was used to run the Python-based application. The identical environment and hyperparameters were used for the study's execution. 20% of the dataset is utilised for testing, while the remaining 80% is kept aside for training. The image was scaled down to a format of (224 × 224) that is suitable for the architectural structures employed.

Table 1. Hyperparameters settings for VGG16, ResNet-50 and AlexNet CNN models

Hyperparameter	**Value**		
	VGG-16	**AlexNet**	**ResNet-50**
Learning rate	1e – 3	1e – 3	1e – 3
Number of Epochs	25	180	25
Batch Size	8	8	8
Optimizer	Adam	Adam	Adam
Image Size	224 × 224	224 × 224	224 × 224
Weight	ImageNet	ImageNet	ImageNet
Metrics	Accuracy	Accuracy	Accuracy
Loss	Categorical Crossentropy	Categorical Crossentropy	Categorical Crossentropy

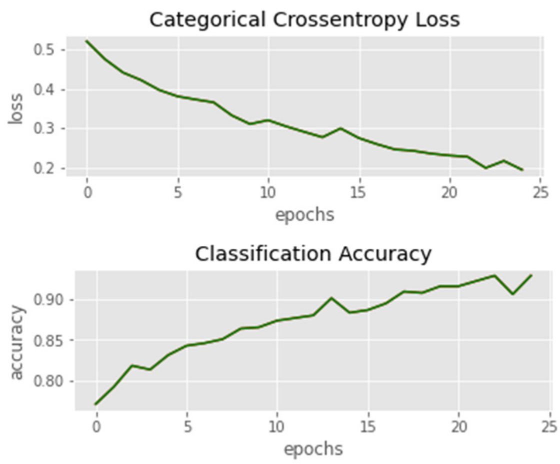


Fig. 4. Graph representing accuracy and loss using the VGG-16 model

From Figure 4, accuracy eventually increases to just over 90%, while loss drops off nicely by epoch 25. Around epoch 15, there is an odd drop in accuracy, although the loss is getting better smoothly and quickly. Categorical cross-entropy is employed as the loss function here to forecast class probabilities.

Progress in both loss and accuracy is shown for the ResNet-50. The model's prediction accuracy is 91% after 100 iterations, and the loss value is also on the decline. There were some variations in the curve for the validation procedure because of the small batch size. The ResNet-50 accuracy is lower than the other CNN models. Accuracy and Loss plots obtained with ResNet-50 architecture are shown in Figure 5.

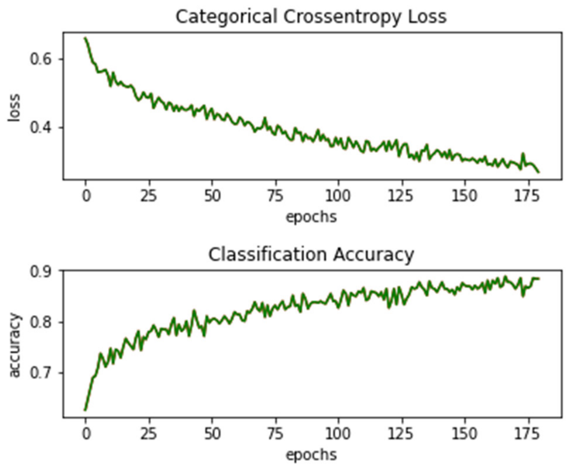


Fig. 5. Graph representing accuracy and loss using the ResNet-50 model

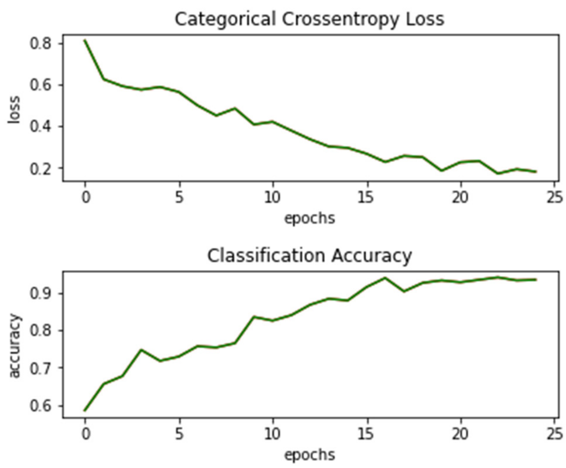


Fig. 6. Graph representing accuracy and loss using the AlexNet model

Figure 6, AlexNet provides better prediction performance when differentiated from other models for example, the precision and recall values of AlexNet is high compared to other models. So, the accuracy and precision values could be upgraded by still enlarging the rate of learning of other models.

Table 2 shows that AlexNet design provides the highest accuracy, at 96.1 percent, compared to 94.16 percent for VGG-16 and 91.56 percent for ResNet-50. Similarly, a precision of 98% is obtained using AlexNet architecture against 94% obtained VGG-16 and 92% obtained using ResNet-50. Sensitivity and Specificity of 93.33 and 100% respectively is reported by AlexNet architecture against Sensitivity and specificity of 93.33% and 94.68% respectively obtained using VGG-16 and 83.33% and 96.81% obtained using ResNet-50. And lastly, F1-Score of 96% is obtained using AlexNet against 94% using VGG-16 and 91% using ResNet-50.

Table 2. Accuracy result of the VGG-16, ResNet-50 and AlexNet

Model Evaluation Parameter	CNN Model		
	VGG-16	ResNet-50	AlexNet
Accuracy	0.9416	0.9156	0.9610
Precision	0.94	0.92	0.96
Sensitivity	0.9333	0.8333	0.9333
Specificity	0.9468	0.9681	0.9787
Recall	0.94	0.90	0.96
F1-score (%)	0.94	0.91	0.96

From the model accuracy and model loss chart, it can conclude the accuracy and loss of VGG-16 is 94.16% and 0.1952, respectively, whereas the accuracy and loss of ResNet-50 is 91.56% and 0.2676, respectively. The accuracy acquired using the AlexNet model is 96.10%, and the loss is 0.1818 is just less than VGG-16. The detailed comparison of accuracy and loss of three models is shown in Figure 7 and performance analysis is shown in Figure 8.

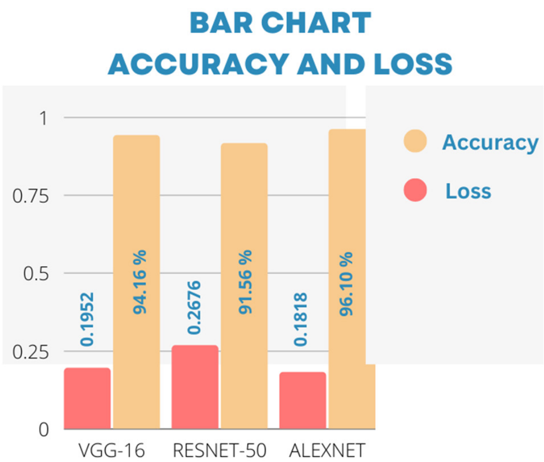


Fig. 7. Comparison of accuracy and loss among different model

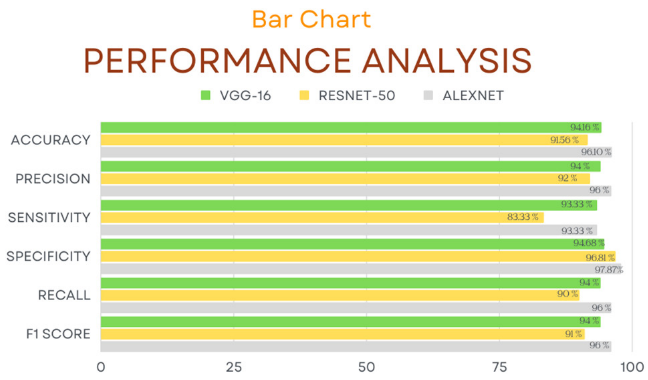


Fig. 8. Performance analysis chart

Based on Table 3 there is a confusion matrix for each approach. The highest True Positive belongs to VGG-16 and AlexNet, 56, while the lowest True Negative is VGG-16, 89. The lowest False Negative belongs to AlexNet as it has 2 positives, while the ResNet-50 has the highest False Positive, 10.

Table 3. Confusion matrix of the VGG-16, ResNet-50 and AlexNet

Confusion Matrix		Predicted Values								
		VGG-16			ResNet-50			AlexNet		
		(+) ve	(–) ve	Total	(+) ve	(–) ve	Total	(+) ve	(–) ve	Total
Actual values	(+) ve	56	4	60	50	10	60	56	4	60
	(–) ve	5	89	94	3	91	94	2	92	94
	Total	61	93	154	53	101	154	56	98	154

3.2 Comparison between existing works

Table 4 compares the current study project with the previous research project (N. Ahmad and K. Dimililer, 2022) [15]. Brain MRI images from Kaggle by Navoneel Chakrabarty' used to detect brain tumors are the data set used in these two experiments. In this work, the effectiveness of the suggested algorithms was evaluated using brain MRI scans for brain tumour identification. Previous study employed four methods: VGG-16, CNN, ResNet-50, and Inception-v3. Meanwhile, current research uses three of the four methods as previous studies, except for CNN and Inception-V3, which AlexNet has replaced.

Researchers used machine learning to predict MRI brain tumor images with a balanced accuracy of approximately 98% on the validation and test set. InceptionV3 scored 48.85%, ResNet-50 scored 45.75%, VGG 16 scored 99.94%, and CNNs scored 97% for classification accuracy.

As a result, the classification accuracy in the current project success obtained from the VGG-16 was 94.16%, ResNet-50 was 91.56%, and AlexNet was 96.10%. This accuracy was attained by using techniques like dropout, data augmentation, and Adam optimization, among others. The reason of a big difference in the accuracy results for ResNet-50 between this paper and previous paper due to different hyperparameters, that can be tuned such as learning rate, batch size and weight decay. The different experimental setup and randomness factor also could affect the accuracy results. The randomness factor may happen during initialization of weights and biases.

Table 4. Comparison between existing works

	Previous Project (N. Ahmad and K. Dimililer. 2022)				**Current Project**		
Dataset	Kaggle				Kaggle		
Method	VGG-16				VGG-16		
	CNN				RESNET-50		
	RESNET-50				ALEXNET		
	INCEPTION-V3						
Accuracy	**VGG-16**	**CNN**	**RESNET-50**	**INCEPTION-V3**	**VGG-16**	**RESNET-50**	**ALEXNET**
	99.14%	97%	45.75%	48.85%	94.16%	91.56%	96.10%

The detection of brain tumors using deep learning tools has several implications for the patient. The patient's chances of survival and quality of life can be greatly increased by early detection and treatment of brain tumours. This is due to the fact that brain tumours can seriously harm the brain, resulting in symptoms including headaches, seizures, and cognitive decline. Brain tumours can grow and spread to other areas of the brain if they are not treated, making them more difficult to treat.

Accurate brain tumour diagnosis utilising deep learning algorithms can aid surgeons in better planning and performing operations. As a result, there may be less possibility of post operative complications and more likelihood that the tumour will be successfully removed.

The other important issues related to the investigation of brain tumor are stability, scalability, trustworthiness and privacy. For stability, the deep learning model must be dependable and stable. Performance of the model should be unaffected by the preparation methods and datasets used. Stability is important because making medical decisions based on inaccurate predictions could have catastrophic consequences.

Secondly is scalability which needs to be scalable to effectively manage enormous volumes of data. In some circumstances, such as in emergency rooms or critical care settings, real-time projections may be necessary. Thirdly is trustworthiness which refer the deep learning solution can be trusted. The model should be interpretable and consistent with medical knowledge. The last issue is privacy where the deep learning solution should be designed to protect patient data and comply with relevant regulations and standards. It is important to ensure that patient data is not compromised during data collection, storage, or analysis.

4 Conclusion

In conclusion, the goal of this effort was to determine if the individual has a brain tumour by combining CNN model classification issues. Performance is assessed using the accomplishment of the issue description, the aim, and the project's scope. The criteria of accuracy, recall, precision, and F1 score determined the success of the AlexNet architecture on the test dataset. The training and testing studies revealed that the AlexNet model outperforms VGG-16 and ResNet-50 in terms of accuracy. The number and organisation of its layers are the key distinctions between the AlexNet design and other CNN systems. Performance may also be directly impacted by the loss and activation functions utilised in the design. When the accuracy value of the AlexNet approach was compared to earlier comparable experiments, it was discovered that the AlexNet method performed well.

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