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ORIGINAL

AI-Powered brain tumor classification and predictive system using convolutional neural networks model

Sistema de clasificación y predicción de tumores cerebrales impulsado por IA basado en redes neuronales convolucionales

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ABSTRACT

One of the most dangerous forms of cancer, brain tumors are brought on by abnormal cell partitioning that is not only uncontrolled but also abnormal. Recent developments in deep learning have been of great use to the healthcare industry, notably diagnostic imaging technology, which is used to diagnose a wide variety of illnesses. There is a good chance that task CNN is the deep learning model that is applied the most frequently and extensively for image recognition. In a similar manner, images obtained from brain MRI scanning are classified by our research team through the utilization of CNN, data augmentation, and image processing approaches. Through the use of CNN, we tested the performance of the scratch CNN model. Despite the fact that the analysis was conducted on a relatively small dataset, the findings reveal that our model's accuracy is quite successful and has incredibly low complexity rates. It achieved an accuracy of 99,5 %, which is significantly higher than the other machine learning.

Keywords: Brain Tumor; Disease Prediction; Tumor Disease; MRI Images; Deep Learning Model and Disease Classification.

RESUMEN

Los tumores cerebrales, una de las formas más peligrosas de cáncer, se producen por una partición celular no solo incontrolada, sino también anormal. Los recientes avances en aprendizaje profundo han sido de gran utilidad para la industria sanitaria, especialmente la tecnología de diagnóstico por imagen, que se utiliza para diagnosticar una amplia variedad de enfermedades. Es muy probable que la CNN de tareas sea el modelo de aprendizaje profundo que se aplica con mayor frecuencia y amplitud para el reconocimiento de imágenes. De manera similar, nuestro equipo de investigación clasifica imágenes obtenidas de resonancias magnéticas cerebrales mediante la utilización de CNN, aumento de datos y enfoques de procesamiento de imágenes. Mediante el uso de CNN, probamos el rendimiento del modelo CNN scratch. A pesar de que el análisis se realizó sobre un conjunto de datos relativamente pequeño, los resultados revelan que la precisión de nuestro modelo es bastante satisfactoria y presenta unos índices de complejidad increíblemente bajos. Alcanzó una precisión del 99,5 %, significativamente superior a la de otros modelos de aprendizaje automático.

Palabras clave: Tumor Cerebral; Predicción de la Enfermedad; Enfermedad Tumoral; Imágenes de Resonancia Magnética; Modelo de Aprendizaje Profundo y Clasificación de la Enfermedad.

INTRODUCTION

There are many different kinds of cells that make up the human population. The functions of each cell are distinct. In order to generate new cells, the cells in the body undergo a process of development and division. The human body's health and function are both improved as a result of these newly formed cells. Cells expand in an unregulated manner when they lose the ability to govern their own growth. It is the mass of extracellular tissue that produces a tumor that is referred to as a tumor. There are two types of tumors: benign and malignant. Benign tumors do not cause cancer, in contrast to malignant tumors, which are known to cause cancer. Important diagnostic factors include medical image data obtained from a wide variety of biomedical devices that make use of a variety of imaging modalities.[1]

Magnetic resonance imaging, also known as MRI, is a technique that may identify magnetic flux vectors and radiofrequency pulses in the nuclei of hydrogen atoms that are contained within the water molecules of a patient's physiological system. Because the MRI scan does not include the use of radiation, it is superior to the CT scan in terms of diagnostic accuracy. The magnetic resonance imaging (MRI) is a diagnostic tool that radiologists can use to evaluate the brain. The MRI has the ability to identify the presence of brain malignancies.[2] Moreover, the presence of the operator in the MRI may lead to the classification of the data being incorrect due to the presence of noise. Because of the enormous volume of MRI data that needs to be evaluated, automated methods that are less expensive are required. The automatic diagnosis of cancers on magnetic resonance images is extremely important since dealing with human life requires a high degree of precision. This is the reason why it is so important.[3]

The classification of magnetic resonance images of the brain as either normal or diseased can be accomplished through the utilization of both supervised and unsupervised machine learning algorithm techniques. Through the application of machine learning techniques, this work offers a powerful automatic categorization methodology for brain magnetic resonance imaging (MRI) data. For the purpose of classifying magnetic resonance images of the brain, the supervised machine learning approach is utilized.[4,5]

The remainder of the content of the article is organized as described below. In the second section, we investigate the numerous methods that have been set up for recognizing and forecasting the detection of brain tumors. In Section 3, we will present the deep learning framework that was developed for the purpose of classification and prediction of brain tumor detection. The findings of the experiment are discussed in Section 4. Finally, conclusions along with potential future developments are discussed in Section 5.

Literature survey

Avsar and Salcin[6] presented a method for detecting brain cancers in their early stages. Analyzed MRI scans were used to identify regions that contain tumors and classify these regions based on various types of tumors. Deep learning produces highly accurate outcomes for image classification. In this study, the CNN technique was employed and executed using the TensorFlow framework as a result. Empirical evidence has demonstrated that the expedited CNN technique achieves a 91,66 percent accuracy rate, surpassing previous investigations.

Abiwinanda et al.[7] employed a basic convolutional neural network (CNN) structure to classify the three prevalent brain tumor types (glioma, meningioma, and pituitary). They achieved a maximum validation accuracy of 84,19 %. This was feasible since the cancers were specifically classified as glioma, meningioma, and pituitary tumors. Ayadi et al.[12] proposed the utilization of a computer-assisted diagnosis (CAD) system that relies on convolutional neural networks (CNNs) for the classification of various brain tumor kinds. The trials utilizing the 18-weighted layered CNN model achieved a classification accuracy of 84,74 % for brain cancer kinds and 90,35 % for tumour grades. The investigations carried out on the three distinct datasets produced these results.

The authors Kokila et al.[8] developed an MRI tumor detection model. The process begins with localizing the tumor and continues with determining its grade and kind as well as its precise location. A single model was utilized by our technique to organize brain MRI data for many categorization tasks, rather of a separate model for each task. Since CNN can classify and detect tumors, it is possible to rely on these capabilities for the multitask categorization. The 92 % accuracy in localizing brain tumors might be achieved using a CNN-based algorithm.

In order to identify and categorize brain tumors, Kaplan et al.[9] employed both approaches. Both the local binary pattern (LBP) based on neighboring angles and the local binary pattern (nLBP) based on neighbourhood distance relations were proposed. The MRIs of the three most common types of brain tumors—glioma, meningioma, and pituitary tumor—were preprocessed using these two methods. Preprocessed photo statistics were utilized for character development. Compared to more traditional feature extraction methods, this updated model performed better. In order to automate feature learning from MRI brain images, Gumaei et al.[10] employed a deep convolutional neural network (CNN) model with six learnable layers. Several MRI classifications are amenable to the suggested strategy, which requires minimal preprocessing and does not use handmade features.

Proposed technology

There is a specific type of neural network known as the Convolutional Neural Network. Its design is based on the idea of a biological neuron known as the receptive field, which is intended to replicate the connectivity pattern of neurons found in the human brain. The CNN model is a feed forward neural network, which consists of a stack of filters (convolutional layer) and sub-sampling layers (pooling layer) that repeat themselves in an alternate manner. Additionally, it comprises one or more neurons that are entirely linked (fully connected layer/dense) at the very end of the network.

In spite of the fact that this model is utilized in a variety of fields, it nevertheless achieves optimal results when applied to image processing applications. Concatenating separate blocks or layers is the method by which the CNN is constructed. The components of these levels are coming together in order to carry out a number of duties. An illustration of the general architecture of the conventional convolutional neural network can be found in figure 1. This network is composed of the following layers.

- Feature Extraction Stage
- Feature Reduction Stage
- Flatten Stage
- Fully Connected Layer
- Soft-max classifiers

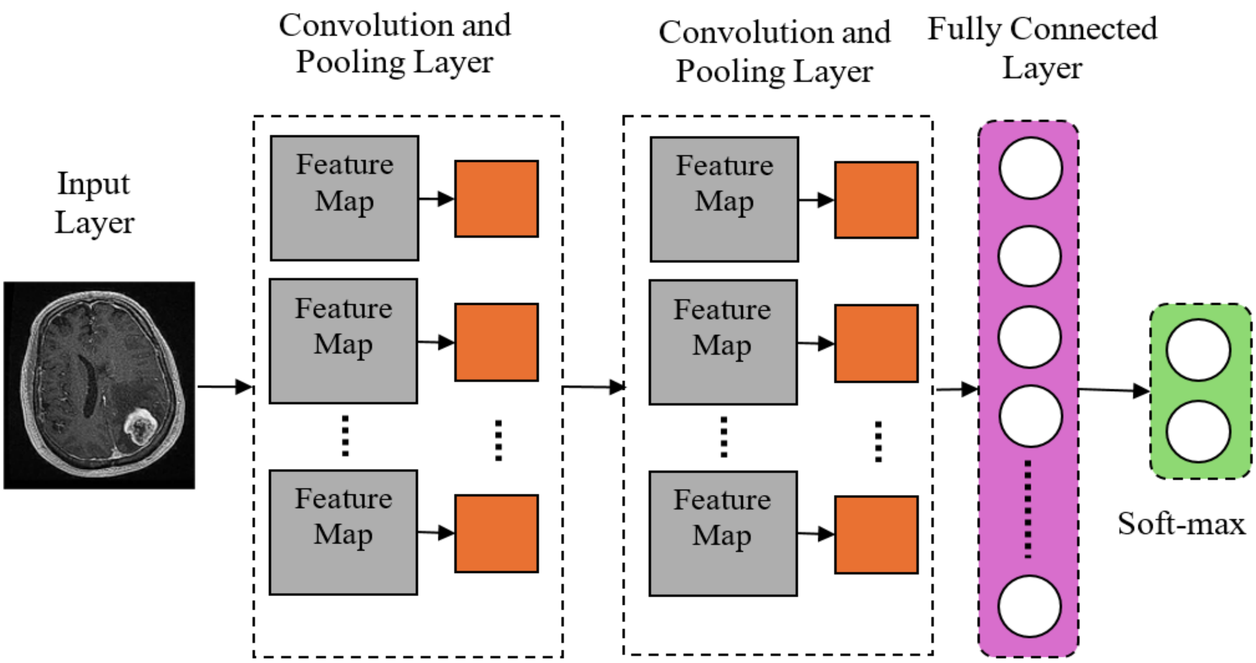
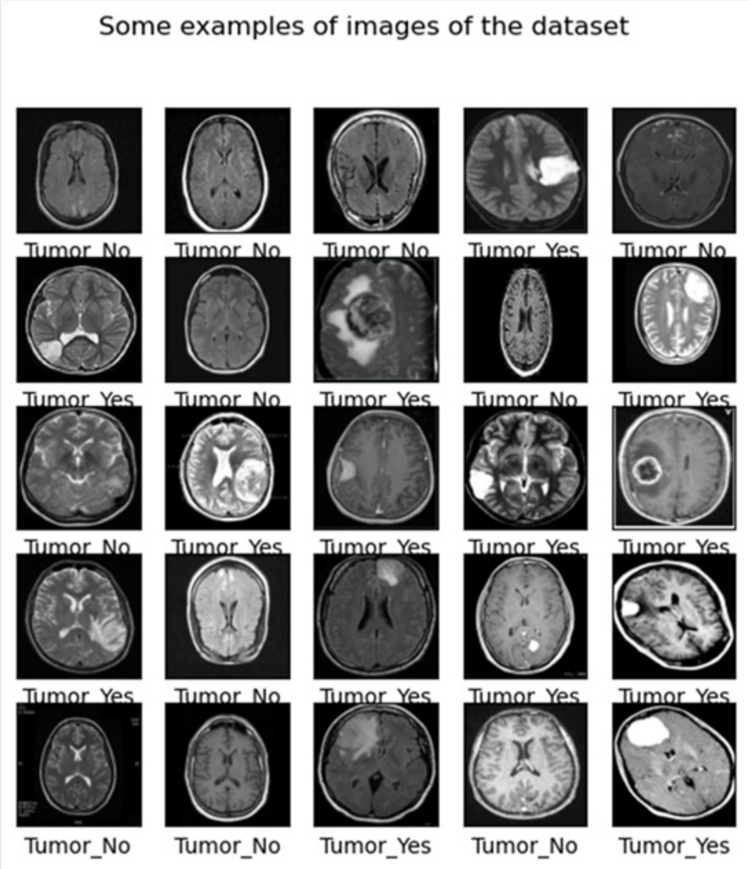


Figure 1. The architecture of Brain Tumor Disease Prediction Model

Dataset Collection

MRI images of individuals with a wide variety of tumor types, including tumor_no and tumor_yes are included in the dataset for this study's representation of brain tumors. A two types of malignant tumors, including tumor_no and tumor_yes are also included in the data collection. The MRI images are subjected to preprocessing and normalization activities before being incorporated into the model. Every one of the two categories contains a total of 1 500 MRI images, making the total number of MRI images 3 000. All of the images are rendered in monochromatic monochrome and have a dimension of 176 by 208 pixels. The tumor_no is labeled c1 and a tumor_yes is labeled c2.[11]

As examples, figure 2a presents a number of magnetic resonance imaging (MRI) pictures taken from the Kaggle repository dataset. A training set, a validation set, and a test set were each created from the data set that was split up. The utilisation of 80 % of the dataset for the purpose of training the model, 10 % for the purpose of verifying the model, and 10 % for the purpose of testing the model is demonstrated in table 1 and figure 2b.



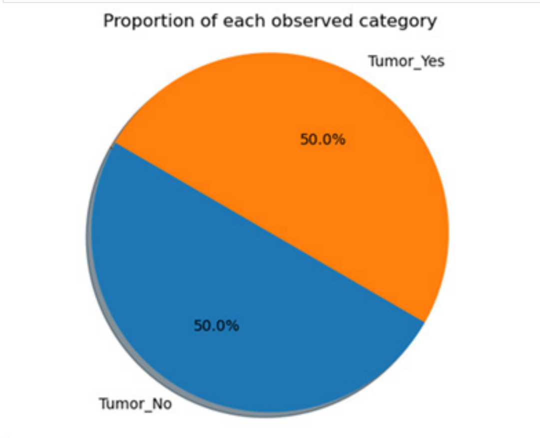


Figure 2. a Sample dataset information with label details **b.** dataset splitting ratio

Table 1. Dataset split ratio

S. No.	Disease Type	Tr. Images	Val. Images	Test	Total	Category
1.	Tumor_No	1200	150	150	1500	C1
2.	Tumor_Yes	1200	150	150	1500	C2

RESULTS AND DISCUSSIONS

The findings of the research on brain tumor disease detection and identification in MRI images are analyzed in this section, which uses CNN models from the deep learning techniques to the work that was done. It was Python and the Anacondo integrated development environment that were used to construct the framework that was offered. This was processed on a computer that has a hard disk that is 1 terabyte in size, 8 gigabytes of random access memory (RAM), and an Intel Core i5 processor.

Performance Metrics

The effectiveness of the suggested solution is evaluated through the use of performance assessment measures. It is possible to employ metrics like as Precision (Pr), Recall (Re), Accuracy (A), and F1-measure (F) in order to evaluate the effectiveness of convolutional neural networks model.

Accuracy: With the help of the accuracy statistic, we can see what percentage of instances were correctly tagged (positive and negative) out of all the instances in the dataset.

$$\text{Accuracy} = \frac{\text{TP+FP}}{\text{TP+FP+TN+FN}} \quad (1)$$

Precision: The positive predictive value of a model is the proportion of accurate positive predictions to the total number of positive predictions it generates. It demonstrates the model's accuracy in detecting genuine positive results as opposed to false positives.

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

Recall: Recall is a metric used to measure the frequency with which a model accurately predicts a positive outcome. It is a quantitative measure used to evaluate the model's ability to correctly identify true positive instances while minimizing the occurrence of false positive instances.

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

F1-Score: The F1 score is a scalar value that balances precision and recall. Simultaneously considering accuracy and memory is beneficial.

$$\text{F} = 2 * \frac{\text{Precision}*\text{Recall}}{(\text{Precision+Recall})} \quad (4)$$

The purpose of this research is to discuss the findings of an experiment in which a deep learning model was utilized to provide a classification and prediction of brain tumors. We will put the model through its paces to determine how effectively it can recognize different types of tumors and award a malignancy score to each of them. As part of the experiment, the model will first be trained on a collection of MRI images taken from brain tumors, and then it will be tested on a separate set of data.

In order to begin, we have trained and evaluated the CNN model in order to classify brain tumor disease in MRI scans before moving on to the next step. We arrived at the conclusion that the CNN model was the approach that achieved the maximum achievable accuracy of 99,5 % and was the most effective strategy. This result was reached on the basis of the data that was presented in table 2 and figure 4.

Table 2. Performance Accuracy of CNN_Tumor Model

S. No.	Model	Acc.	Pre.	Rec.	F1-Sc.
1.	CNN Tumor_model	99,5	99,5	99,5	99

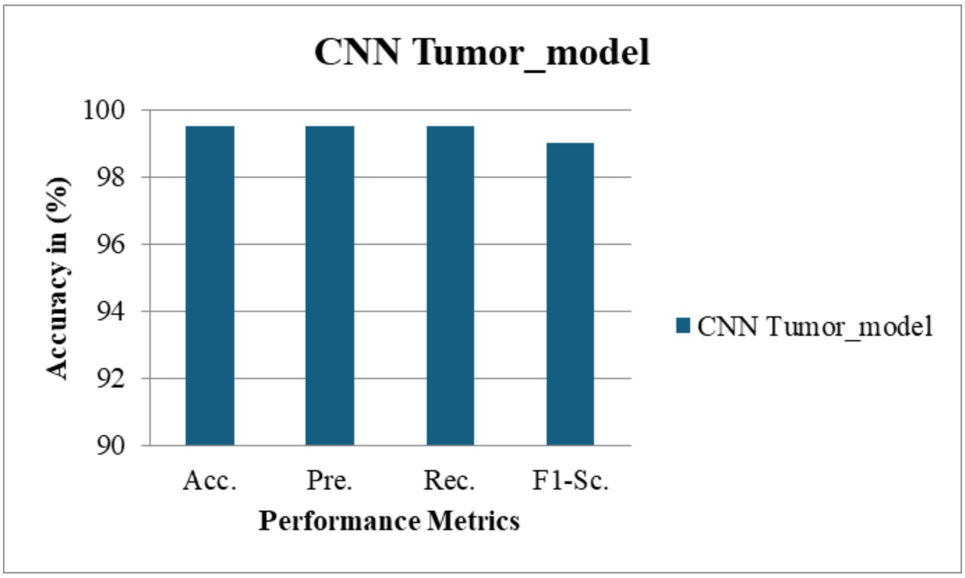


Figure 3. Performance Accuracy of CNN_Tumor Model

Figure 4 presents the results of a CNN model after 15 epochs: trained accuracy, validated accuracy, trained loss, and validated loss. These results are displayed in terms of conventional metrics such as trained accuracy and validated accuracy. It is necessary to construct these parameters in order to provide the information in order to provide an estimation of the trained models by making use of a learning rate of 0,00001 and SGD optimization. These parameters are calculated in order to provide an estimation of the degree to which the training models have been overfit. This estimation is provided in order to supply the training models with a degree of overfitting.

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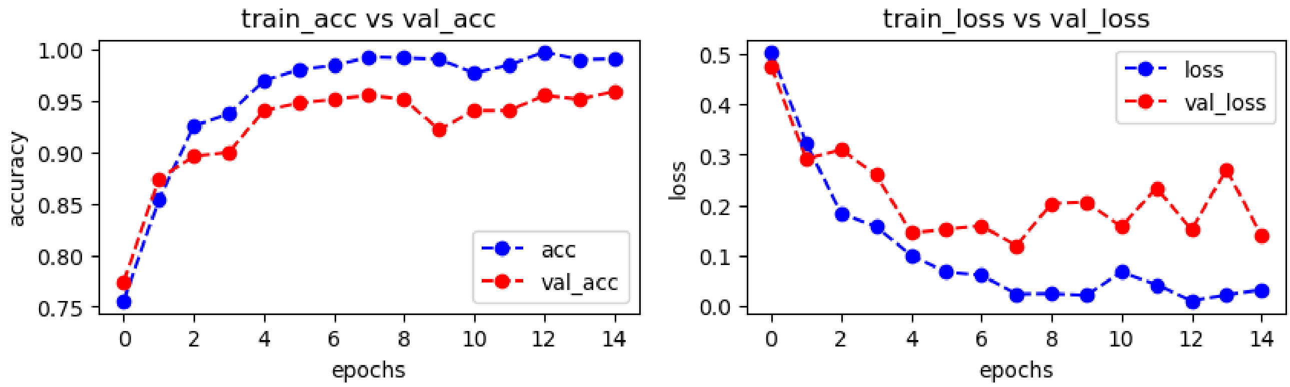

Figure 4. Training and Testing accuracy and loss

As can be seen in figures 5a and figure 5b, the confusion matrix's results are displayed, along with the predictions that were made regarding the classification of brain tumors and the prediction of illnesses.

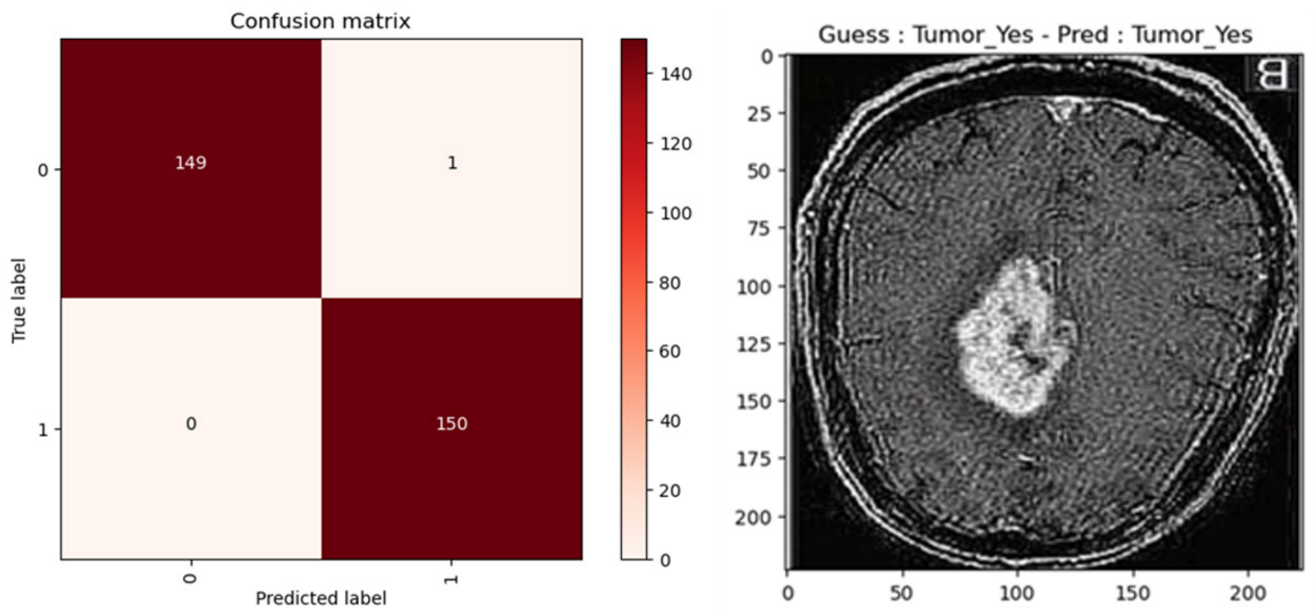

Figure 5. a Confusion Matrix of CNN_Tumor, **b.** Prediction results

CONCLUSIONS

The area of machine learning research and study has expanded beyond the realm of feature engineering and into the realm of architectural design as a result of recent advanced developments in deep learning. This study presents a method for binary classification diseases by making use of Convolutional Neural Networks (CNN) models. The goal of this research is to facilitate the early detection of brain tumors.

The effective CNN models have been designated for the purpose of classifying brain tumors in medical imaging. When it comes to the detection of brain tumors, a high degree of accuracy, say 99,5 %, is achieved. For the purpose of determining whether or not their preliminary screening for numerous forms of brain tumors is accurate, medical professionals and radiologists can make use of the CNN models that were produced as part of this research. In future, we have planned to implement the model with multi-class classification as well as implement in GPU configuration.

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Data curation: Sivamurugan V.
Formal analysis: Sivamurugan V.
Research: Sivamurugan V.
Methodology: Sivamurugan V, Radha N.
Project management: Sivamurugan V.
Resources: Radha N.
Software: Swathika R.
Supervision: Sivamurugan V.
Validation: Radha N, Swathika R.
Display: Swathika R.
Drafting - original draft: Radha N, Swathika R.
Writing - proofreading and editing: Sivamurugan V, Radha N.