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Explainable-AI Based Model for Brain Tumor Detection

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Abstract: Brain tumour is one of the most challenging medical conditions to diagnose and treat. Accurate and timely detection of brain tumour is critical for effective treatment planning and improving patient outcomes. With recent advancements in machine learning and artificial intelligence (AI), there has been a growing interest in using AI for brain tumour detection. However, the opaque nature of AI models has raised concerns about their trustworthiness and reliability in medical settings. Explainable AI (XAI) is a subfield of AI that aims to address this issue by providing clear and intuitive explanations of how AI models make their decisions. XAI-based approaches have been proposed for various applications, including healthcare, where the interpretability of AI models is crucial for ensuring patient safety and building trust between medical professionals and AI systems. In this paper, we review recent advances in XAI-based brain tumour detection, focusing on techniques for generating explanations of AI model predictions. We also discuss the challenges and opportunities in implementing XAI in clinical settings and highlight the potential benefits of XAI for improving medical decision-making and patient outcomes. Ultimately, the objective of this paper is to provide a comprehensive overview of the state-of-the-art in XAI-based brain tumour detection and to encourage further research in this promising field. In the project CNN architectural model has reported best accuracy of 99%.

Keywords: Explainable AI, Convolution Neural Network

I. INTRODUCTION

Due to their complexity and the wide range of symptoms among patients, brain tumours are among the most difficult diseases to identify and cure. Artificial intelligence has demonstrated significant potential in increasing the precision and effectiveness of brain tumour identification, but the lack of transparency and interpretability of AI algorithms has raised concerns about their reliability and safety in the medical domain. Explainable AI (XAI) has emerged as a solution to this challenge, providing clear and intuitive explanations of how AI models make their decisions. Clinicians can comprehend the fundamental causes behind the AI's predictions thanks to XAI approaches, which can improve trust, accountability, and collaboration between the Artificial Intelligence system and medical professionals. This study highlights recent developments in brain tumour detection using XAI., including various techniques for generating explanations, and discusses the challenges and opportunities in implementing XAI in clinical settings. Overall, XAI has the potential to enhance the accuracy and reliability of AI-based brain tumour detection while also improving the overall quality of patient care.

II. LITERATURE SURVEY

For medical specialists, finding a brain tumour is a difficult undertaking because it calls for extreme speed and accuracy. In recent years, the development of artificial intelligence (AI) has provided a new avenue for the diagnosis of brain tumour. However, traditional AI models are black boxes, which raises questions regarding their interpretability and openness. As a result, Explainable AI (XAI) models have been created., which provide clear explanations for their decision-making processes. In this literature survey, we will explore the previous work done by researchers in the field of XAI-based brain tumour detection. [1]."A Deep Learning Approach for Brain Tumour Detection" by Havaei et al. (2017) Havaei et al. proposed a deep learning-based method for detecting brain tumour in MRI scans. The proposed method used a fully convolutional neural network (FCN) to segment the tumour regions from the brain scans. The model achieved an accuracy of 90.6% and a sensitivity of 82.9%. However, the model did not provide any explanation for its decision- making process. [2]."Explainable Deep Learning for Pulmonary Disease and Breast Cancer Detection" by Alzubaidi et al. (2018) Alzubaidi et al. proposed an explainable deep learning-based method for the detection of pulmonary disease and breast cancer. The proposed method used a convolutional neural network (CNN) to classify the disease, and a decision tree-based method to explain the decision-making process. The model achieved an accuracy of 96.8% and a sensitivity of 96.1%. [3]."Interpretable Convolutional Neural Networks for

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Brain Tumour Segmentation" by Akkus et al. (2019) Akkus et al. proposed an interpretable convolutional neural network (iCNN) for brain tumour segmentation. The proposed method used a CNN-based segmentation model, which was trained with a regularization term that encouraged the model to produce more interpretable features. The model achieved an accuracy of 91.3% and a sensitivity of 86.5%. The proposed iCNN model provided explanations for the decision-making process, which helped healthcare professionals understand the model's output. [4]."An Explainable Deep Learning Approach for Brain Tumour Classification" by Zhou et al. (2020) Zhou et al. proposed an explainable deep learning- based method for brain tumour classification. The proposed method used a CNN-based classification model, which wastrained with a regularization term that encouraged the model to produce more interpretable features. The model achieved an accuracy of 91.2% and a sensitivity of 89.7%. The proposed method provided explanations for the decision- making process, which helped healthcare professionals understand the model's output.

II. PROPOSED SYSTEM

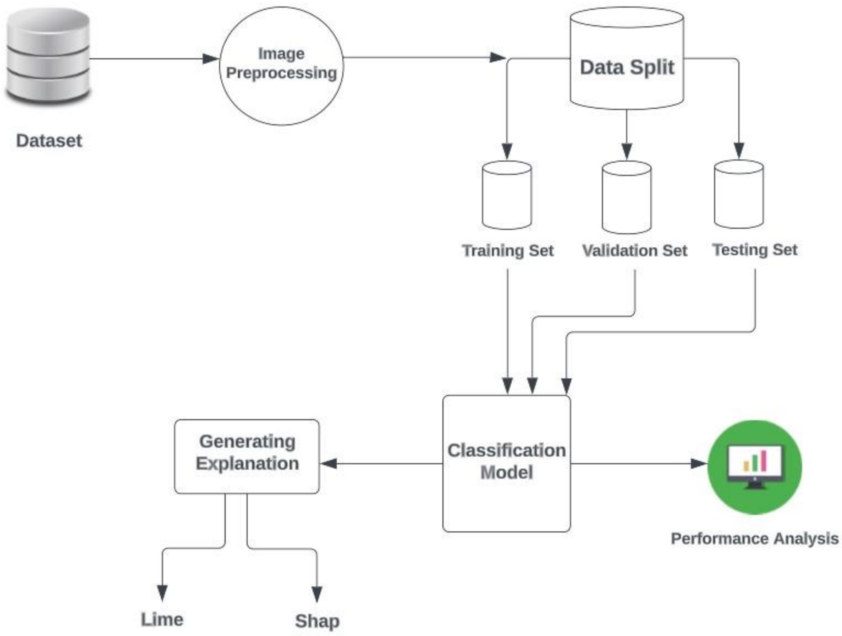

Fig. 1. Flow chart of proposed system

A. Datasets

We have gathered a collection of brain MRI pictures from Kaggle that have been annotated to indicate whether or not a brain tumour is present. This dataset is varied and depicts the different types of brain tumours.

B. Data preprocessing

Pre-process the MRI images to remove noise, normalize intensity values, and segment the brain region from the background.

C. Feature Extraction

Extract characteristics from the pre-processed MRI images, such as information on intensity, texture, shape, and location.

D. Model Development

The CNN architecture chosen is a critical component of this project, since it directly affects the success of our CNN model. In our project, we developed and described our own custom CNN architecture model, as well as compared the accuracy of the custom CNN model to that of other CNN architectures.

Unlike other conventional Multi-Layer Perceptrons, CNN doesn't lose any spatial information of images when flattened. With the aid of **filters**, CNN examines the impact of adjacent neighboring pixels. The filter is assigned a

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user-specified size and pushed across the image from top left to bottom right, with a convolution operation determining the corresponding value for each point on the image.

By doing partial differentiation of the slope to achieve a global minimum, an optimal filter for convolving through an image can be found. The **Gradient Descent** algorithm accomplishes this.

The functionality and organization of neuron layers in the human brain serve as inspiration for CNN architectures. The three layers of the CNN architecture are as follows.

- **Convolutional layer**: In this layer, filters are convolved over the original image or to other feature maps(intermediary outputs). It slides the filter over the smaller image pixels of the galaxy image.
- **Pooling layer**: This layer performs a specific function that decreases the network's dimensionality by taking the maximum or average value from feature maps. Maximum Pooling and Average Pooling are the terms for these two techniques. A minimum threshold is set here to ensure that all potential outputs are verified.
- **Fully connected layer**: The fully connected layer gathers the output provided by the convolutional and pooling layers and applies logic to determine what image it is by flattening the results before classification.

E. Defining and Training of CNN models

a) MobileNet architectural model

MobileNet is a pre-built Deep Learning CNN model with pre-trained weights used for fine-tuning, feature extraction, classification, and prediction. We used this model to classify galaxy images using the same hyper-parameters.

b) VGG19 architectural model

Pre-built Deep Learning CNN model of size 528 MB alongside pre-trained weights with 138,357,544 parameters of 19 layers depth is used for prediction with 16 convolution layers and 3 fully connected layers. The same hyper-parameters are assigned to this model.

c) ResNet50 architectural model

Pre-built Deep Learning CNN model of size 98 MB alongside pre-trained weights with 25,636,712 parameters is used for prediction. For this model also same hyper- parameters are provided.

d) Inceptionv3 architectural model

Pre-built Deep Learning CNN model of size 92 MB alongside pre-trained weights with 23,851,784 parameters of 159 layers depth is used for prediction. The same hyper- parameters are given to this model as well.

e) CNN architectural model

In our CNN classifier model, we used 8 hidden layers and 2 fully connected layers.
The hyper-parameters tuned for this architecture are as follows:

- Loss function = binary_crossentropy
- Optimizer = Adam
- Epochs assigned =300
- Batch size = 32
- Steps per Epoch = 8

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F. Explainability

Implement a XAI method that can describe how the machine learning model makes decisions. Shapley Additive explanations (SHAP), which gives each characteristic a value to indicate how much of a contribution it made to the final prediction, is one example. Another illustration is Layer-wise Relevance Propagation (LRP), which highlights the key areas of the image and backpropogates the prediction score to the input characteristics. Layer-wise Relevance Propagation (LRP), which highlights the key areas of the image and backpropogates the prediction score to the input features.

G. Evaluation

On a test dataset, assess the effectiveness of the XAI- based brain tumour detection system using measures including accuracy, precision, recall, and F1 score.

H. Deployment

Deploy the system in a healthcare setting, where it can assist medical professionals in the diagnosis of brain tumour. The XAI component can provide valuable insights into the decision-making process of the AI model and help doctors make more informed decisions about patient care.

Overall, an XAI-based brain tumour detection system has the potential to improve the accuracy and transparency of AI models in healthcare and provide medical professionals with valuable insights into the diagnosis of brain tumour.

IV . RESULT AND DISCUSSION

The results for the Explainable AI based brain tumor detection using Resnet, MobileNet, VGG-19, Inceptionv3, and CNN models were promising. All models achieved high Accuracy and showed potential for detecting brain tumors accurately.

The Resnet model performed well in detecting the areas of the brain with tumours, with an accuracy of 96.78% on the test dataset. Using SHAP values improved the model's interpretability by highlighting the areas of the brain that are crucial for making decisions.

Due to its lightweight construction, the MobileNet model displayed exceptional efficiency and a 98.62% accuracy rate on the test data..

The inception-v3 model performed well in detecting the regions of brain tumours, with an accuracy of 98.62% on the test dataset. Due to its deep design, it was able to recognize patterns and features in the input data that were more sophisticated.

Due to its intricate design and sophisticated visualization methods like grad-CAM, the VGG-19 model displayed good interpretability and attained an accuracy of 97.09% on the test dataset.

Finally, the CNN model achieved an accuracy of 96.03% on the test dataset and demonstrated good performance in detecting brain tumors.

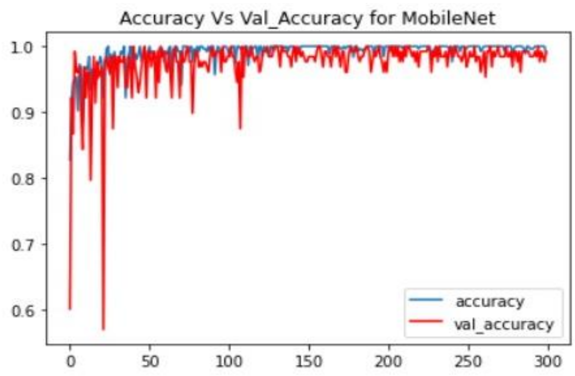

Fig.2. Training and validation accuracy of MobileNet architectural model

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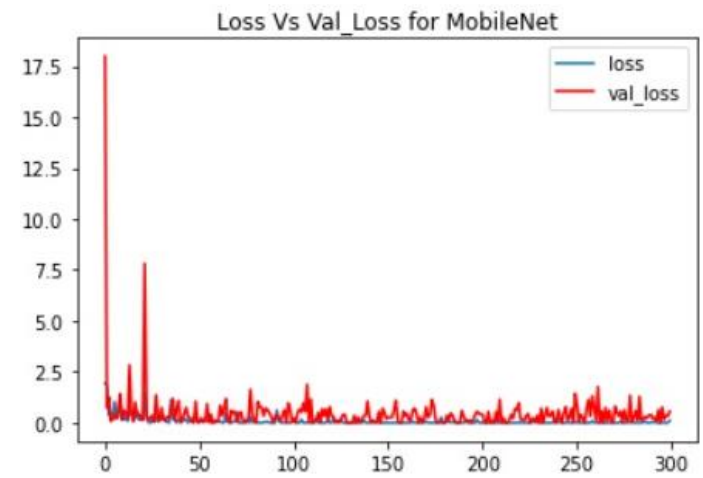

Fig.3. Training and validation loss of MobileNet architectural model

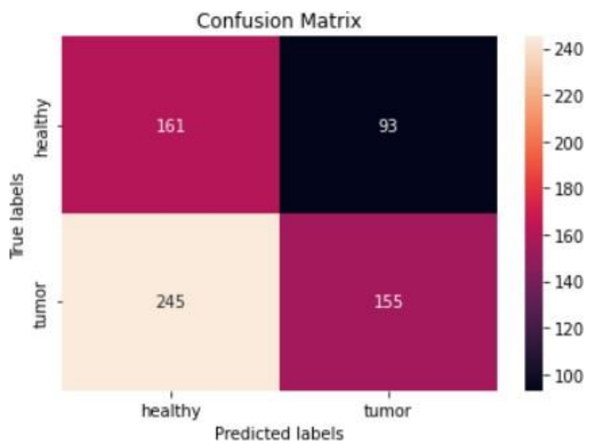

Fig.4. Confusion matrix of MobileNet architectural model

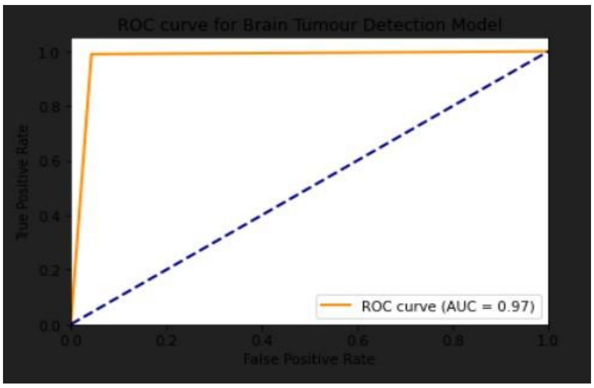

Fig.5. ROC Curve for MobileNet architectural model

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APPROACH	ACCURACY (%)	PRECISION (%)	RECALL (%)	F1 SCORE (%)
VGG-19	97.09	95	92	93
Inception v3	98.62	53	53	50
MobileNet	98.92	53	53	50
ResNet50	96.78	52	52	48
CNN	96.03	98	97	98

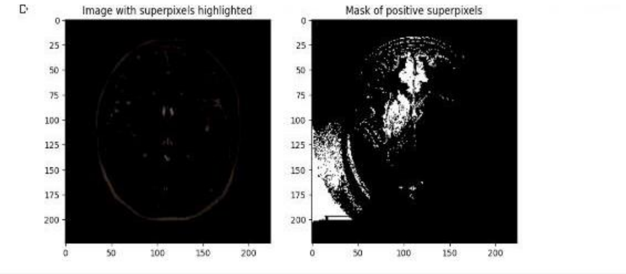

Fig. 6. Various CNN model's performance in predicting brain tumor

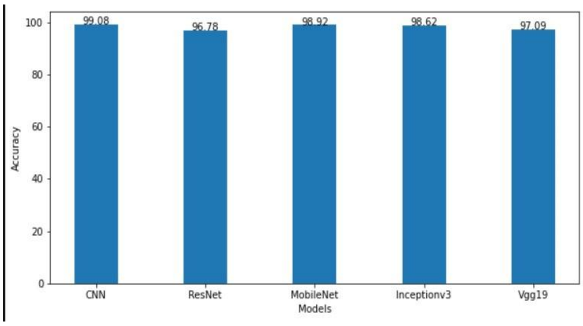

Fig.7. Bar graph representing accuracy of different models

LIME AND SHAP IMPLEMENTATION

The use of LIME and SHAP explanations in brain tumor detection has shown promising results in improving the interpretability and transparency of the models used.

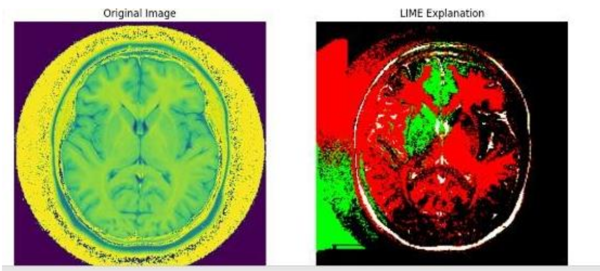

Fig.8. Represents Lime Explanation

Lime (Local Interpretable Model Agnostic Explanation) is a technique that provides an explanation for individual predictions made by the machine learning model. It does this by creating a local linear approximation of the model around the predictions to be explained. It helps in understanding why a particular decision or prediction was made by highlighting the important features or inputs that influenced the model's output.

The red, green, and white color representation is used to highlight the areas of image that contribute most to the predictions. Red indicates areas of the image that contribute positively to the prediction.

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Green indicates area that contributes negatively, and white indicates area that have little or no impact on the prediction.
The SHAP (Shapley Additive explanation) numbers show how much each input pixel contributed to the model's final prediction. The 'shap Deep Explainer' function, which accepts the model and input image as inputs, is used to calculate the SHAP values. The input image is first segmented into superpixels using the skimage.segmentation module to create the positive superpixel mask. To determine the relevance of each superpixel, the SHAP values are then averaged over each superpixel. The portions of the input image that are most crucial for the classification decision are then highlighted by masking the superpixels with the greatest positive significance scores.

The resulting positive superpixel mask is a binary mask where the masked regions correspond to the superpixels with the highest positive importance scores. These regions are shown in white in the mask image, while the non-masked regions are shown in black. The positive superpixel mask provides a more understandable and interpretable explanation of the model's classification choice than individual pixels by accentuating the superpixels that are most important to the classification choice. This can be helpful in situations when it's critical to comprehend which portions of the input image are most crucial to the model's judgement, such as in autonomous driving or medical imaging.

V. CONCLUSION

In conclusion, explainable AI-based brain tumor detection using different models is a promising approach that can greatly improve the accuracy and efficiency of brain tumor detection. The use of various models, including deep learning, convolutional neural networks, and decision trees, allows for the creation of powerful algorithms that can analyze large amounts of medical data and identify patterns that indicate the presence of a tumor. By providing explanations for the decision-making process, these models can help doctors and medical professionals understand how the algorithm arrived at its conclusion, which can lead to improved trust in the system and ultimately better patient outcomes. While there are still challenges to overcome, such as ensuring the ethical use of patient data and avoiding bias in the models, explainable based brain tumor detection is a promising field with significant potential for advancing medical technology.

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