Exploring the Potentials of Explainable AI for Early Cataract Detection to Foster Accessible Healthcare

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Abstract:

Explainable AI (XAI) aims to provide transparency and comprehensibility in ML models' decision-making processes, enabling users to understand why a model makes specific predictions or decisions. This transparency feature is crucial for building trust in Ai systems, especially in high-stake applications such as healthcare, finance, and autonomous vehicles etc. In this research article, we aim to explore the capabilities of explainable AI for one of the critical use cases in the domain of ophthalmology for cataract prediction.

Cataract is a common yet prevalent eye disease which is affecting millions of individuals across the world. It is essential to detect and treat this disease early to prevent vision loss and enhance the quality of life. By advancing diagnosis accuracy and efficiency, artificial intelligence (AI) has the potential to detect cataract based on the fundus image of an eye and other possible parameters. This can act as a decision support system for an ophthalmologist or general medical practitioner, especially in remote areas which are lacking high-end scientific equipment. However, the opacity and complexity of advanced AI models make them difficult to adapt such systems in actual clinical practice. Explainable AI (XAI) techniques if applied to such advanced ML models can address this issue by allowing healthcare practitioners to comprehend the decision-making process of AI models. This article reviews the critical explainable AI techniques and their possible application for one of the use cases – cataract detection.

Keywords: Explainable AI, Interpretable AI, Transparent AI, Cataract Detection, Deep Learning.

I. Introduction

Cataract is one of the leading causes of visual impairment and blindness worldwide. Cataract is the most common cause of blindness in India, accounting for approximately 62% of all occurrences [1]. 90% cases affected by cataract and are partially or fully blind are from developing countries [2]. However, in such cases over 75% of vision loss is curable, suggesting that roughly four out of every five cases are reversible [2]. Late-stage eye disorders always

cause significant visual acuity impairment, which might be permanent [2]. As a result, early detection and prevention of cataracts can help in the avoidance of vision impairment and blindness.

In recent years, artificial intelligence (AI) and machine learning (ML) have emerged as promising technologies to improve the accuracy and efficiency of cataract detection. Deep convolutional neural networks have produced excellent results in CACD (Computer-aided Cataract Diagnosis) techniques. However, deep convolutional neural networks require large datasets to be accurate. Gathering large datasets for real-time training is time-consuming and sometimes impossible. As a result, rather than training a CNN from scratch, transfer learning approaches based on pre-trained CNNs are typically preferred. The pre-trained CNN-based CACD algorithms are trained on millions of natural images before being transferred, allowing for fine-tuning to enable cataract detection with small datasets. In fact, it is faster and easier to fine-tune a pre-trained CNN than to train a deep CNN from scratch with randomly initialized weights. However, the lack of interpretability and transparency of AI models is a major barrier to their adoption in the healthcare domain. Explainable AI (XAI) techniques aim to address these issues by comprehending the AI models' decision-making processes. XAI approaches are intended to make AI more transparent and interpretable, allowing healthcare practitioners to comprehend the reasons behind AI decisions and build trust in these systems.

By offering explanations for the model's predictions, XAI approaches can aid in the conversion of black-box models to clear-box models. A black-box model is an AI model whose internal workings are not visible to the user or creator. The model makes predictions or decisions, but it is unclear how those predictions are made. A clear-box model, on the other hand, allows the user to comprehend how the model makes its predictions. This is significant because it helps users have confidence in the model's output and a deeper understanding of the elements that drive its judgments. By applying XAI approaches, we can acquire insights into how black-box models make decisions and increase our understanding of the factors that drive those decisions. This can not only help in improving the transparency and accountability of AI models' decisions but will also help to build trust among the consumers of their output.

In this paper, we present a comprehensive literature survey of research work done for cataract detection and XAI techniques in healthcare. We discuss the benefits and drawbacks of different cataract detection systems as well as various AI models and XAI methods used in the healthcare domain. We also look at the challenges and potential of integrating these technologies into clinical processes, such as the requirement for user-friendly and interpretable XAI techniques that healthcare practitioners with varied degrees of technical experience can understand. Our review also emphasizes the significance of ethical considerations in the development and implementation of AI-powered cataract detection systems.

Additionally, the possible impact of XAI techniques on AI system adoption and acceptance in healthcare as well as their ability to improve patient outcomes and quality of life is also discussed in this article. The findings from this research can help guide the development of more effective and clinically relevant cataract detection systems, as well as the incorporation of AI and XAI approaches into clinical practice. Overall, this paper contributes to the growing body of literature on AI and XAI in healthcare and provides insights into the challenges and opportunities of implementing these technologies in the context of cataract detection.

II. Literature Review

A. Literature Review of Cataract Detection Techniques

The authors of the paper [2] proposed a cataract detection system using a convolutional neural network with a pre-trained VGG-19 model on a dataset that consisted of fundus images of 800 patients. The dataset consisted of images of varied sizes, so OpenCV was used to resize the image to 224*224 pixels. A VGG-19 pre-trained CNN model was applied to pre-processed images to classify cataract and normal eye images. The Adam optimization algorithm was used to reduce the cost function and improve the performance of the model.

The authors of the paper [3] proposed to develop an Android application for cataract detection using the Cascade Classifier library. First, images of the eye are captured by placing smartphones in front of the eye at a distance of not more than 30cm. Then, the cascade classifier was used to detect and crop the pupil out of an image. The system used this RGB value of the pupil to compare with the database value of the cataract's RGB value to detect the cataract.

The authors of the paper [4] experimented with cataract detection using an eye image analysis based on luminance. The luminance-based technique extracts the luminance value of an image by using pixel brightness transformation. In the experiment, 100 eye images were taken: 50 from healthy eyes and 50 from diseased eyes. To remove noise from the images, the median filter and watershed algorithms were used. The SVM classifier was used to differentiate between healthy and diseased eyes.

The authors of the paper [5] proposed a hybrid convolutional and recurrent neural network (CRNN) for the detection and classification of cataracts according to their severity. A dataset of 8030 high-quality fundus images was captured without flash and with auto white balance and classified into four categories namely normal i.e., no cataract, mild, moderate, and severe. The proposed CRNN divided the dataset into several subsets, and each subset was fed to pre-trained CNN models. The extracted features were then combined using global average pooling and finally fed into LSTM for classification into four classes. The authors obtained 97\% accuracy.

The authors of paper [6] put forth a New Angular Binary Pattern (NABP) for extracting the texture features. Following the extraction of features, the author proposed a kernel-based CNN. The author discovered some flaws in convolutional layers and attempted to solve them. For example, convolution layers reduce the number of weights, which reduces memory usage, resulting in faster computation and less overfitting of the dataset. After comparing the proposed and existing systems, 97.3\% accuracy is achieved.

The authors of paper [7] proposed a method for automatically grading cataracts based on a patient's eye video. The dataset consists of a cataract video with a length of less than 10 seconds of 76 eyes, i.e., 38 people were collected using the slit lamp method, and 1520 images were extracted from this video. iSpector Mini is video collection equipment used to collect the dataset. The proposed method uses the YOLOv3 algorithm to classify the cataract by automatically identifying the position of the lens. An accuracy of 94% and an F1 score of 0.9388 were achieved using the proposed method.

The authors of the paper [8] proposed a classification technique for ocular diseases using a dense correlation network, DCNet. This classification task is based on paired colour fundus

photographs (CFPs). DCNet is made up of a backbone convolutional neural network that extracts feature representations from the paired CFPs, a spatial correlation module that captures the dense correlation between features of the paired CFPs and fuses relevant feature representations, and a classifier to produce a disease score. The dataset consists of 3500 eye sample images. Each of the 3500 patients has been classified into eight categories. The images are first resized to 512x512, and then 448x448 images are cropped randomly. The final score and F1 score are 0.827 and 0.913, respectively, when ResNet—101 is used as the backbone CNN.

The authors of the paper [9] proposed a cataract classifier where Decision Tree and Bayesian Network are used. Both algorithms are supervised learning algorithms, and tri-learning is employed to discover a sound hypothesis. The wavelet and texture extracted from each fundus image are used to calculate the accuracy of the classifier. It was observed that the wave feature performed better than the texture feature. A dataset of 5378 fundus images was used to classify cataracts into four grades according to their severity: non-cataract, mild, moderate, and severe. Total accuracy of 88% and 70% were achieved when Bayesian networks and J48 were used.

The authors of the paper [10] proposed two algorithms, one for classifying the eye into three categories—healthy eyes, mild cataracts, and severe cataracts. And a second algorithm for determining the degree of cataract present in the affected eyes. The author classified an eye as healthy if the mean intensity of the histogram for that eye is below 50 and as having cataracts if its mean intensity is above 100. The second method involves calculating the pupil and cataract areas in an unhealthy eye. The formula used for calculating the percentage of cataracts is:

$$Degree = (cataractarea/(pupilarea+cataractarea))*100 \qquad (i)$$

The authors of the paper [11] proposed an effective network selection method for computer-aided cataract detection in a noisy environment. The suggested method is divided into two parts: first, the input images are pre-processed to reduce noise, and then multiple deep neural networks are trained on the pre-processed images. After that, the trained networks are evaluated using a performance metric, and the best-performing network is chosen for the final diagnosis. The proposed method was tested on a dataset of cataract images with varied amounts of noise, and the findings revealed that the chosen network obtained very high accuracy in noisy environments as compared to other methods. Overall, the proposed method can provide an accurate and efficient solution for cataract diagnosis in noisy situations.

The authors of the paper [12] proposed employing ensemble neural networks and transfer learning to detect and grade cataracts. The proposed method is divided into two stages: first, a pre-trained convolutional neural network (CNN) is utilized to extract features, and then an ensemble of several CNNs is trained to categorize the recovered features into various cataract grades. Using a large dataset of cataract images, the ensemble model is trained using a combination of transfer learning and fine-tuning. The proposed method was tested on two publicly available datasets, and the findings showed that it performed effectively.

The authors of paper [13] proposed a method for detecting cataract disease using deep convolutional neural networks (CNNs). The suggested method entails pre-processing the input images to improve contrast and remove artefacts, then training a CNN on the pre-processed images to categorize them as cataract or non-cataract. The suggested method employs a CNN

architecture that includes several convolutional and pooling layers, followed by fully connected layers for classification. The proposed approach was tested on a dataset of cataract images, and the results showed that it achieved high accuracy.

The authors of the paper [14] developed an optimal hybrid approach for cataract detection that includes image processing techniques and machine learning algorithms. The proposed method involves pre-processing the input images with contrast enhancement and image normalization techniques before extracting features with the grey-level co-occurrence matrix (GLCM) and discrete wavelet transform (DWT). The features gathered are then used to train a cataract detection support vector machine (SVM) classifier. A grid search algorithm is used to identify the ideal combination of SVM hyperparameters to optimize the performance of the SVM classifier. The proposed approach was tested on a dataset of cataract images, and the results showed that it performed well.

The summary of pre-processing techniques, classification techniques learnt from the respective review articles are summarized in Table 1.

Table 1: Analysis of existing techniques for Cataract Detection

Reference No	Pre-processing Technique	Classification techniques	Shortcomings	Accuracy / F1- Score
[2]	OpenCV libraries to resize image to equal size	VGG-19 CNN model	Due to the limited images, they were unable to develop severity grading and identify the exact location of the	97 %
[3]	Cascade Classifier	Matches the color of the pupil with the color of the pupils with cataracts in the dataset	Implemented on a very small dataset of 50 people of which 20 had cataract and 30 were normal	90 %
[4]	Median Filter, Watershed Algorithm	SVM	Only classifies as healthy and diseased eyes. It does not detect the cataract in an eye. Dataset was small and only contained 100 images.	96 %
[5]	Pre-processed images were used	Hybrid Convolutional and Recurrent Neural Network	Time complexity in the proposed system will be greater as the multiple CNN models are used	97 %

[6]	Novel Angular Binary Pattern	Kernel based CNN	Implemented on a very small dataset of 100 cataracts images.	97.3 %
[7]	Densenet model	YOLOv3	Dataset was created using only 38 people which brings the problem of overfitting.	94 %
[8]	OpenCV libraries to resize images to 448 x 448	DCNet – backbone CNN, the SCM and the classifier	Limited interpretation of model, lack of external validation and limited dataset.	F1 Score: 0.827
[9]	Image normalization, Contrast enhancement, Image denoising, Image segmentation and Feature Extraction	Bayesian Network and Decision Tree	pre-processing techniques and limited interpretation.	88 %
[10]	Image acquisition, Image resizing, Gray scaling of Image, Feature Extraction	Histogram is prepared for each image. Images having mean intensity below 50 are healthy and above 100 are affected by cataract	Dataset used is small, manual pre-processing is required	-
[11]	Feature extraction using pre- trained Alex-net model	Locally and globally trained Support Vector Networks (SVN)	Impact of other image distortions such as blur, contrast, etc. is not considered	92.97 %
[12]	Downsized the images into equal sizes with 2048 x 2048 pixels, RGB images normalized between 0 and 1, and used resizing, rotation, shifting, and flipping to obtain additional images.	Transfer learning, ensembles of pre-trained CNN's and stacked LSTM's	Proposed system is not suitable for noisy and low-quality fundus images.	99.20% (normal vs. cataract) and 97.76% (normal to severe)

[13]	Image normalization, augmentation and enhancement and feature extraction	pre- trained VGG-16	The size of the dataset is very small.	97.1 %

B. Literature Review of XAI Techniques

The authors of paper [15] review the current state of explainable AI intelligence (XAI) in the healthcare domain. The authors discuss various XAI techniques, such as rule-based methods like decision trees and decision sets, model-agnostic methods like LIME and SHAP, and posthoc methods like Grad-CAM and Activation Maximization. The authors evaluate the accuracy and interpretability of these methods using publicly available medical datasets, such as the Electronic Health Record (EHR) dataset and the Chest X-Ray dataset. The authors also discuss various XAI approaches, including model-based methods, such as explainable neural networks; decision-based methods, such as counterfactual reasoning; and instance-based methods, such as prototype-based explanation. The authors identify the challenges and opportunities for XAI in the medical domain, such as handling high-dimensional and complex medical data, providing clear and actionable explanations, and integrating ethical and legal considerations into XAI design. The authors conclude that XAI has great potential for improving the accuracy, reliability, and fairness of medical decision-making but also highlight the need for further research and development to fully realize this potential.

The authors of paper [bib16] conducted a review of 223 studies on the application of deep learning-based explainable artificial intelligence (XAI) in healthcare, focusing on anterior and medical imaging modes. The reviewed papers were categorized by the authors, who observed some notable trends. Most studies used post-hoc explanations instead of model-based explanations and employed both model-specific and model-agnostic explanation methods. Additionally, most of the papers provided more local explanations and fewer global explanations. It is not surprising to see these developments given the authors' emphasis on deep learning for analysing medical images. Among the available methods for explaining the predictions made by convolutional neural networks (CNNs), saliency mapping techniques are the most used. These methods offer localized and post-hoc explanations that are specific to the model being used. In addition, unlike model-based XAI techniques, post-hoc methods can be applied after the neural network has been trained, making them easier to use.

The authors of the paper [17] present a study that evaluates the performance of different explainable artificial intelligence (XAI) methods in the medical domain. The authors apply a set of XAI methods, including rule-based methods, model-agnostic methods, and post-hoc methods, to a medical dataset, such as the Retinal Fundus Image Quality Assessment (RFIQA) dataset and the EyePacs dataset. The authors use a panel of medical experts to evaluate the XAI techniques like Grad-CAM and SIDU based on their transparency, interpretability, and accountability. The results of the study show that the XAI methods have different levels of accuracy, ranging from 75% to 85%. The study also reveals that the XAI methods vary in terms

of their transparency, interpretability, and accountability, with some methods providing clear and actionable explanations while others are less interpretable.

The authors of the paper [18] present a system called LISA (Local Interpretable and Simulatable Network-Based Analysis), which attempts to improve the explainability of medical images by combining many current explainable artificial intelligence (XAI) techniques. LISA is intended to enable global and local interpretability of medical images, allowing doctors to understand how a diagnosis was achieved at the image and pixel levels. The proposed approach involves training a convolutional neural network (CNN) on a large dataset of medical images, followed by interpreting the CNN's predictions using numerous XAI techniques such as saliency maps, class activation maps, and layer-wise relevance propagation. The outcomes of the various XAI methodologies are integrated to provide a thorough explanation of CNN's diagnosis. The proposed framework was tested on two publicly available medical imaging datasets and found to have high accuracy and interpretability.

The authors of paper [19] describe RetainVis, a visual analytics tool that analyses electronic medical records (EMRs) and identifies relevant patient information using interpretable and interactive recurrent neural networks (RNNs). Pre-processing the EMRs to extract key clinical traits, which are subsequently used to train an RNN, is the proposed tool. The RNN is intended to capture the temporal relationships between clinical parameters and predict patient outcomes such as hospital readmission or mortality. The RetainVis tool provides a visual interface that enables doctors to interact with the RNN and investigate the key elements and temporal patterns that drive the predictions. To assist doctors in understanding how the RNN makes predictions, the proposed tool contains multiple interpretability strategies, such as attention processes and feature importance scores. The suggested tool was tested on a real-world EMR dataset, and the findings demonstrated that it delivered good accuracy and interpretability.

The authors of the paper [20] proposed an explainable convolutional neural network for glaucoma detection. The processing is performed on color fundus image data. Histogram equalization and contrast-limited adaptive histogram equalization are used to improve the color fundus images. This enhanced image data is used by an explainable convolutional neural network. The XAI was made possible by Class Activation Mapping (CAM), which offers heat map-based explanations for the visual analysis carried out by CNN. The ORIGA-Light retinal image dataset was one of the three datasets used, and it had the highest mean values with an accuracy of 93.5%, a precision of 93.8\%, and an F1 score of 95.7%. This dataset contains a total of 650 retinal image data points, including 168 glaucoma and 482 normal cases.

The authors of paper [21] suggested a new CNN model that is lightweight and can classify images related to COVID-19, pneumonia, and tuberculosis. They have also created a framework for generating explanations for the classifications made by the model. The CNN model achieved high accuracy rates of 94.31% in testing and 94.54% in validation, and the generated explanations were validated by medical experts using SHAP, LIME, and GradCam XAI algorithms. The study suggests that the proposed model, along with XAI, can be useful in identifying and categorizing lung diseases. Compared to existing methods, this model has a simpler architecture and performs better when it comes to classifying CXR images with the help of XAI.

The authors of paper [22] present an explainable AI-driven decision-support system for COVID-19 diagnosis based on fused classification and segmentation. The proposed approach

involves using image enhancement techniques to pre-process chest X-ray images and a convolutional neural network to segregate lung areas. The segmented images are then fed into a fused classification and segmentation model, which predicts COVID-19 infection using an ensemble of multiple CNNs. The proposed method generates saliency maps and attention heatmaps that highlight the portions of the X-ray image that are most relevant for the diagnosis, resulting in an interpretable approach to COVID-19 diagnosis. The method also generates feature importance scores, which assist doctors in understanding which clinical aspects drive the diagnosis. The proposed system was tested on a large dataset of COVID-19 and non-COVID-19 chest X-ray images, and the findings demonstrated that it was accurate and interpretable. Observations on various XAI techniques applied on eyes' images along with their shortcomings analysed and presented Table 2.

Table 2: Analysis on XAI Techniques applicable in the healthcare Domain

Reference No	XAI techniques	Output	Shortcomings
[15]	LIME, SHAP and Grad-CAM		Cannot handle high-dimensional and complex medical data.
[16]	CAM and Grad-CAM		Didn't cover techniques like LIME and SHAP
[17]	Grad-CAM and SIDU	75 % – 80 %	Lesser accuracy, reliability, and fairness of medical decision-making
[18]	LIME, Integrated gradients, Anchors and SHAP	Using CNN and transfer learning, testing accuracy for detecting chest x-rays was around 90%.	False-positive and false-negative results.
[19]	Attention mechanism	For heart failure and cataract, the AUC (Area Under the ROC Curve) is around 95% and 97%, respectively	It has scalability concerns due to its computationally expensive deep learning-based model.
[20]	CAM is used for heat map based explanation for image analysis done by CNN.	On ORIGA-Light retinal image dataset, the accuracy is 93.5%, precision is 93.8% and F1 score is 95.7%.	Other XAI methods can be integrated with similar CNN models, they might have better results than the current findings. Detailed evaluation with humans is still required
[21]	LIME, SHAP and Grad-CAM	Accuracy rates of 94.31% in testing and 94.54% in validation	Trained on small dataset and performance is not tested on large dataset.

[22]	Grad-CAM and Guided Grad-CAM	In GGECS, the classification model proposed has an overall accuracy of 98.51%, while the segmentation model achieves an IoU score of 0.595.	Doctor validation is still required because incorrect output in the case of COVID-19 could result in dangerous circumstances.

III. Proposed Approach

Through this thorough study, we propose a system that uses pre-trained neural networks instead of deep learning networks developed from scratch since they offer the following benefits:

1) Reduced training time: As pre-trained models have already been trained on huge datasets, you can save time and money by bypassing the time-consuming training procedure. You can fine-tune the pre-trained model on your specific dataset in a relatively short period.
2) Increased accuracy: Because pre-trained models have already learned significant features and patterns from huge datasets, they can perform better on your unique task. This is especially true if your dataset is small or close to the data used to train the pre-trained model.
3) Transfer learning: pre-trained models can be used as a starting point for transfer learning, which is the process of adapting a pre-trained model to a new task. Transfer learning can help you exploit the knowledge obtained by the pre-trained model, which is especially valuable if you have little data for your specific task.
4) Generalization: Pre-trained models have been trained on enormous amounts of data and have learned generic characteristics that may be applied to a wide range of tasks. As a result, they can be used for a variety of applications, ranging from computer vision to natural language processing.
5) Accessibility: Because pre-trained models are frequently available as open-source code, researchers and developers can quickly use them. This enables a broader spectrum of people to experiment with and improve on the models, resulting in faster advancement in the field.

After performing classification using a pre-trained neural network, we suggest employing XAI techniques to overcome the black-box model's main drawback and learn how and why a specific conclusion is obtained. Explainable AI techniques fall into two broad methods viz. Model Agnostic and Model Specific both applied at the global level or local level.

- Model-agnostic explanation methods: These methods aim to provide explanations for the predictions of any machine learning model, regardless of the underlying architecture. Examples include LIME (Local Interpretable Model-Agnostic Explanations) and SHAP (SHapley Additive exPlanations).

- Model-specific explanation methods: These methods are designed to provide explanations for specific machine learning models, such as decision trees or neural networks. For example, in the case of decision trees, a model-specific explanation can involve visualizing the tree structure and highlighting the path taken to make a prediction.

When working with image data, there are several techniques that can be employed, and the ideal technique depends on the unique use case and the type of image data involved. Below are some of the most often used XAI technique for image data, along with their advantages and disadvantages presented in Table 3.

1) LIME (Local Interpretable Model-Agnostic Explanations): LIME is a method that produces interpretable explanations for individual black-box model predictions. LIME generates a sequence of perturbations to the original image and trains a local interpretable model on these perturbations to explain the black-box model's behaviour.
2) SHAP (SHapley Additive exPlanations): SHAP is a way of describing any machine learning model's output. It uses Shapley values to determine the contribution of each feature to the model's prediction. SHAP can help users comprehend which pixels of an image contributed the most to a certain categorization decision in the context of image data.
3) Grad-CAM (Gradient-weighted Class Activation Mapping): This technique reveals crucial parts of an image that contributed the most to a neural network's classification judgment. Grad-CAM is frequently used for object detection tasks and can assist users in understanding what features the model looks for when reaching a classification decision.

Table 3: Analysis of LIME, SHAP and Gradient-based XAI techniques.

XAI Techniques	Type of XAI Method	Advantages	Disadvantages
LIME (Local Interpretable Model-Agnostic Explanations)	Global model-agnostic methods	Can be applied to any model and any type of data; provides local interpretability	May not capture global trends; sensitive to perturbations in data
SHAP (SHapley Additive exPlanations)	Global model-agnostic methods	Captures global trends; applicable to any model and any type of data	Computationally expensive for large datasets and complex models
Gradient-based methods	Model-specific methods	Captures feature importance and feature interactions; applicable to any differentiable model	May not provide interpretable explanations for non-differentiable models; may be sensitive to hyperparameters

Generally, the optimal XAI technique for image data is determined by the unique use case and type of image data. It is frequently advantageous to employ a combination of techniques to acquire a thorough understanding of how the model makes predictions

It is crucial to highlight that there is no "better" XAI technique for image data because each has its own set of strengths and shortcomings and may be better suited to different use cases.

Nonetheless, the following are some probable reasons why Grad-CAM may be preferable over LIME and SHAP in some situations:

1) Grad-CAM highlights crucial regions in the image that contributed to the model's classification conclusion, making it simple to visually analyse and comprehend what features the model seeks. LIME and SHAP, on the other hand, generate perturbations or feature importance that are not directly related to image regions, making it more difficult to analyse and explain why a model generated a specific prediction.
2) Grad-CAM is built exclusively for convolutional neural networks (CNNs) used in image classification tasks; hence, it may be more tuned for this sort of data than LIME and SHAP, which are model-agnostic and can be applied to any type of model.
3) Grad-CAM can be used to create heatmaps that depict the most relevant regions of an image for a specific classification decision, making it simple to communicate findings to non-technical stakeholders. LIME and SHAP, on the other hand, produce features of importance or disturbances that may be more difficult to visualize and express well.
4) Grad-CAM captures feature importance and feature interactions and hence it is applicable to any differentiable model. However, it may not provide interpretable explanations for non-differentiable models and can be sensitive to hyperparameters

However, to select appropriate XAI technique, it is critical to evaluate the use case and requirements of the business domain problem, as each method has its own set of trade-offs and limitations as discussed before.

A. Prospects and Challenges in XAI Adoption.

The adoption of Explainable AI (XAI) in clinical and medical practices faces several challenges. There are various obstacles to Explainable AI's (XAI) acceptance in clinical and medical settings. One of the most significant obstacles to XAI approaches in healthcare is a lack of standardization and norms. Various XAI methodologies have varied strengths and drawbacks, and healthcare practitioners' levels of skill in evaluating and understanding AI models may vary. As a result, defined criteria and standards for the development and validation of XAI models in healthcare, as well as training and education for healthcare professionals on how to interpret and apply these models, are required.

Another challenge is the requirement for XAI techniques that are easy to use and interpret. AI models can be complicated to comprehend, particularly for healthcare professionals with limited technical knowledge. As a result, XAI methods must be created with usability in mind so that they are accessible and understood by a broad range of users. This includes using visuals, natural language explanations, and interactive interfaces to allow users to communicate with AI models.

Concerns about privacy and security are also significant barriers to the use of XAI in healthcare. Patient data is extremely sensitive; therefore, XAI models must be designed and applied in a manner that safeguards patient privacy and data security. Furthermore, AI models are susceptible to bias, which might result in unfair and discriminatory results. As a result, addressing these challenges through responsible AI practices such as data governance, transparency, and accountability is critical.

The lack of interoperability and connection with established clinical workflows is also a big obstacle when it comes to XAI adoption in healthcare. To be effective, AI systems must be smoothly integrated into clinical workflows, which involves significant investment in terms of resources, infrastructure, and training.

Using XAI in clinical settings may necessitate significant resources, including financial investment and healthcare professional training. Cost and resource constraints may limit XAI's use in healthcare.

Furthermore, given the specific situation and the audience, the XAI approach and the level of information in the explanation must be carefully chosen. For example, if the model is being used for clinical decision-making, the explanation should be precise and particular, whereas a shorter and more generic explanation may suffice for regulatory compliance.

Finally, the verification and validation of XAI results by a medical professional are critical steps in ensuring the AI system's safety, efficacy, and ethical application in clinical and medical practices. Even if the XAI model is highly accurate, there may be biases, flaws, or restrictions in the data or the model that, if not recognized and remedied, could lead to wrong or dangerous conclusions.

Therefore, the use of XAI in healthcare necessitates a careful evaluation of the aforementioned problems as well as the creation of interpretable, transparent, and ethical and legal XAI methodologies. Collaboration between technological experts, healthcare professionals, and regulatory organizations is required to achieve this.

IV. Conclusion

AI not only has the capabilities to assist a human in its day to day decisions but also has the potential to improve the quality of a life for a mankind. Healthcare is a domain which is still reluctant to adapt the AI capabilities in the early diagnosis and treatment despite of its higher accuracy, amidst its opacity towards understanding the rationale behind the autonomous predictions and decision. In healthcare domain, if AI based systems are equipped with explainable AI techniques, then clinician and medical experts will be able to leverage the potential use of AI for early diagnosis of critical diseases like cataract, cancer, or tumour etc. Explainable AI based system deployed on portable devices can help the healthcare experts to take the facility towards remote places to treat the under-privilege people fight against these critical diseases.

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