Enhanced Breast Cancer Prediction using Soft Computing and XAI

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***Abstract*—Interpretable AI is critical for constructing trustworthy systems, particularly in sensitive areas like breast cancer analysis, where patient outcomes are at stake. Many current AI models prioritize complexity and predictive accuracy, often at the cost of interpretability. This paper introduces an integrated approach combining Fuzzy Inference Systems (FIS), SHAP (Shapley Additive Explanations), and Grad-CAM (Gradient-weighted Class Activation Mapping) to create more interpretable and reliable breast cancer prediction models. FIS provides rule-based reasoning, allowing clinicians to trace the AI's decision-making process step by step. SHAP offers insights into the impact of each feature, clarifying how factors such as age or tumor size contribute to the prediction. Grad-CAM produces visual heat maps highlighting key areas in medical images, such as mammograms, showing clinicians where the model focused during diagnosis. This integrated approach improves both transparency and accuracy, providing clinicians with a reliable, interpretable decision-support system. By making AI predictions in breast cancer analysis more understandable, this method enhances trust in AI-driven healthcare, ultimately leading to better patient outcomes through informed, reliable diagnostic tools.**

***Keywords:* FIS, Grad-CAM, SHAP.**

I. INTRODUCTION

AI in healthcare, maximum particularly in the prediction of breast cancer, has many capability elements. but, for AI to be commonly time-honored and located to apply in scientific conditions, it needs to end up interpretable. This has triggered an growth in the rise of explainable AI or XAI which focuses on making AI systems obvious. even though advanced AI fashions, together with deep neural networks, frequently show off very excessive accuracy, they may be additionally what might be known as "black boxes"-little or no notion into how they without a doubt make selections. This has problematic implications in the problem of medicine, wherein every sufferers and physicians need clear notion into what reasoning leads to a diagnosis or prediction. Interpretable interpretability is, consequently, one critical element in building don't forget with AI-pushed scientific system. primary among those are model-agnostic and version-particular techniques. model-agnostic methods imply applying strategies like SHAP (SHapley Additive motives) and LIME (neighborhood Interpretable version-agnostic reasons) throughout exclusive fashions for rationalization of the way input capabilities, be they scientific statistics or imaging effects, have an effect on AI model predictions. for instance, SHAP can offer an cause of how age of the affected individual or the dimensions of the tumour would upload to the overall rating for the danger due to breast most cancers. model-unique methods are for specific architectures of AI structures. as an example, selection wooden offer a very readable and rule-primarily based explanation of what's causing the real prediction by the use of making clinicians see the motive inside the again of the motive that the model is making step-clever. All of those interpretability strategies collectively can also moreover increase accuracy and make AI models obvious to help early detection of breast cancer and decorate custom designed treatments. A transparency of such nature among healthcare carriers based on informed choices results within the most right care of sufferers at the same time as paving the manner for confidence in AI structures.

II. RELATED WORK

Enhancing explainable synthetic intelligence for illness prognosis: A thorough assessment of fuzzy inference machines with interpretable fuzzy rules [1] Saikit Lam, Jin Cao, Ta Zhou, and Shaohua Zhi [1]
Growing trustworthy AI within healthcare, and with particular applications ranging from lab research to hospital settings, requires interpretable AI, also known as explainable AI. While being a critical factor for AI research, the increasing complexity and accuracy of highly precise models often supersede the importance of interpretability-skill, thereby limiting trust and

applicability within delicate fields such as clinical analysis. FIS are such emergent tools that together with usability offer to fill up in the real world a gap connected with fuzzy rules comparable to a way thinking that has been presented by humans. However, few studies devote themselves to discussing FIS' ability to provide scientific predictions concerning various kinds of clinical facts that might include a sequence indicator, pix, and tabular statistics. This review discusses how fuzzy policies are compared with other techniques related to interpretability strategies dealing with those multimodal facts types and how the developed fuzzy policy can be adapted in accordance with those extraordinary datasets. via equipping high-good quality practices and making destiny research orientations, the assessment aims to increase the usability and reliability of AI in scientific prognosis.

Breast cancer prediction based on neural networks and additional tree classifier the usage of function ensemble gaining knowledge of [2] Deepti Sharma , Rajneesh Kumar , Anurag Jain [2] most cancers prediction stays a large project for healthcare specialists, with early detection being vital for well timed analysis and treatment. on this test, the writer introduces an current characteristic combining ensemble studying with neural networks and extra timber for classifying breast cancer into benign (non-cancerous) and malignant (cancerous) instructions. the use of the Breast most cancers Wisconsin (Diagnostic) dataset from the gadget mastering repository, the proposed approach's regular ordinary performance is classed using numerous metrics, inclusive of class accuracy, specificity, sensitivity, bear in thoughts, precision, F-degree, and Matthews correlation coefficient (MCC). The results show tremendous normal performance, carrying out a real accuracy price of ninety nine.seventy four%. furthermore, the Neural community and similarly Tree (NN-ET) model surpasses special superior classifiers primarily based definitely mostly on several traditional standard universal performance metrics, showcasing its effectiveness in breast most cancers magnificence.The study's experimental simulations and statistical analyses validate the version's efficiency and spotlight its blessings over existing system mastering processes within the literature, positioning it as a promising device for enhancing breast cancer prognosis.

Deep gaining knowledge of algorithms for the early detection of breast cancer: A comparative take a look at with conventional system studying [3] Rolando Gonzales Martinez , Daan-Max van Dongen [3] This study explores the application of deep knowledge retrieval in prescreening breast cancer with respect to several information pieces, including demographic statistics, biochemical markers from blood samples, and risk factors. functionality selection was applied to a dataset made up of 64 cancer patients and 52 healthy controls to uncover relevant predictors. good-fold Monte Carlo pass-validation established deep learning to work better than traditional system training as it provides minimum false-negative rate and the propagation of uncertainty in making predictions. The proposed methodology is a radiation-free, non-invasive, and cost-effective alternative to imaging-based screenings: it can identify those who require further testing and catch malignancy at earlier stages, thus freeing healthcare.

Breast most cancers Detection and Prevention using system mastering [4] Arslan Khalid, Arif Mehmood, Bader Fahad Alkhamees[4] The main cause of female death in the developing world is breast cancer, for which early detection and treatment are of utmost importance and tends to present mainly as invasive ductal carcinoma and ductal carcinoma in situ. new technological capabilities in artificial intelligence and machine learning have allowed for the means of creating accurate diagnostic models, significantly those that take advantage of MRI and convolutional neural networks. This work proposes an efficient deep knowledge model for breast cancer detection in automated mammograms of different densities. Additionally, it also includes three methods of function selection: low-variance feature elimination, univariate function selection, and recursive feature elimination, utilizing both craniocaudal and mediolateral views. The variant was found to be based on a dataset of 3,002 images of 1,501 patients who had their virtual mammography between February 2007 and May 2015. Six type algorithms—random forest (RF), decision tree (DT), ok-nearest neighbors (KNN), logistic regression (LR), support vector classifier (SVC), and linear SVC—established a high degree of efficiency and accuracy, using less computational strength for the diagnosis of breast cancer.

Breast most cancers prediction using gated attentive multimodal deep getting to know [5] Safak Kayikci & Taghi M. Khoshgoftaar [5] The most important issue for fitness awareness among women is breast cancer, which affects one in eight ladies within their lifetime. Early detection is the key to increasing the success of treatment, and thus efforts to identify associated genetic predispositions are highly recommended; however, facts about genes are very complex, creating challenging scenarios due to the volume of functions involved. This study presents an attention-based multimodal deep learning model that incorporates medical information, copy number variations, and gene expression profiles to improve breast cancer prediction. The proposed model utilizes the attention mechanism, by which the model would be able to search mammography images properly for even the most subtle patterns of cancer indication, in combination with patient demographics such as age and family history to improve the predictive accuracy. The method is dependent on two stages: the former of those utilizes sigmoid gated interest convolutional neural network to learn stacked capabilities, while the latter one uses pulling down, dense layers, and dropout for bi-modal consideration. And what is obtained from the results, this approach does broad complementarity for detection and analysis of breast cancers, helps advance patient outcome.

Breast most cancers Malignancy Prediction the use of Deep studying Neural Networks [6] Sidharth S. Prakash; ok. Visakha [6] most cancers regularly conjures up fear because of its undeniably lethal nature, but early prognosis and right treatment can make certain correct outcomes. pc-assisted evaluation (CAD) is an increasing number of getting used as an effective preliminary screening approach for several diseases, inclusive of most cancers. This paper elaborates at the layout of a deep neural network for malignancy prediction in breast most cancers. with the usage of the Wisconsin breast most cancers dataset from the UCI repository, have a look at implements optimizes strategies fending off overfitting with the aid of using the strategies which include early stopping and dropout layers. the strategies make certain that version gives extraordinary performance and effects in scoring of extra than ninety-8 F1 rating value. this indicates of high overall performance underlines the ability of deep learning strategies to improve breast cancer detection and diagnosis, hence finally translating into better affected person results.

III. ARCHITECTURE DIAGRAM

Using fuzzy inference structures, explainability approaches, and machine learning, the following diagram illustrates an all-around information processing and decision-making pipeline: inputting facts in, then sending them through a preprocessing layer which makes the information understandable while also assuring the quality and consistency of facts entered. At the feature extraction stage, following the cleaning of the records, a CNN recognizes and extracts important styles and features from the data. These extracted functions are prepared using a knocking down layer in order to have them ready for further processing. All the above processed data are then applied to a Fuzzy Inference machine, which provides an intermediate result by using fuzzy common sense to deal with the uncertainty that may be involved in the data. This output is further divided for use of explanation technique, which includes SHAP (SHapley Additive explanations) and Grad- CAM (Gradient-weighted elegance Activation Mapping) applied to interpret functionalities most inspiring the model's decisions. It, therefore, carries the insights gathered within those explanation techniques towards producing a final choice with transparent and interpretable outcomes that beautify consideration and knowledge of the consumers regarding the outputs of the version.

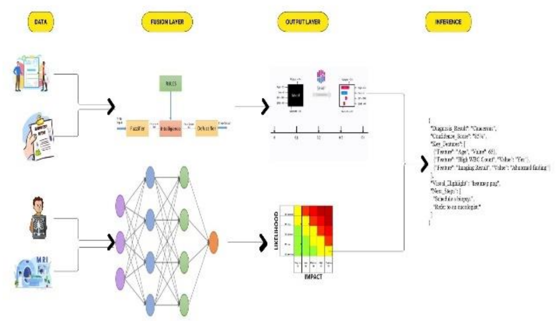

Fig. 1. Pipeline for cancer prediction using fusion of FIS and CNN

IV. PROPOSED SYSTEM

The system applied improves the ease of cases analysis and prediction of most breast cancers, as it employs CNN with FIS and the application of explainability tools like Grad-CAM and SHAP. This method might be used to evaluate the accuracy of such clinical images as mammograms and breast MRI based on the scoring to be provided for validating malignant tumors. This technology allows for the use of CNNs in the analysis of clinical images, including breast MRI scans and mammograms, accompanied by the accurate classification of malignant tumors. The device develops complex pattern recognition in imaging data through the application of edge deep learning techniques, which promotes greater precision in diagnoses, allowing for the early diagnosis of the majority of breast malignancies. Meanwhile, FISs reason via rules while analyzing medical information like the test results and affected individual records that helps healthcare practitioners with their decisions precious assistance. The two-pronged method allows a better understanding of every graphic and clinical information regarding breast cancers, thus helping clinicians make the extremely informed diagnoses. For further beauty in the interpretability of the model's predictions, the system employs SHAP and Grad-CAM. SHAP (SHapley Additive factors) reveals the importance of many abilities and guides doctors to what factors of the reports are most influential in their lead predictions. Grad-CAM extends this by providing a visual idea of what areas, in this case, areas in the medical snap shots are contributing to the version's selection-making manner. together, these tools cultivate an evident and trustworthy diagnostic environment, ensuring that healthcare professionals have the knowledge needed to make informed decisions in breast cancer diagnosis and ultimately improve patient care. A class of deep learning system specifically designed for visual statistical processing are convolutional neural networks or CNNs. They are useful for photograph category tasks because they have multiple layers that regularly learn to extract hierarchical capabilities from

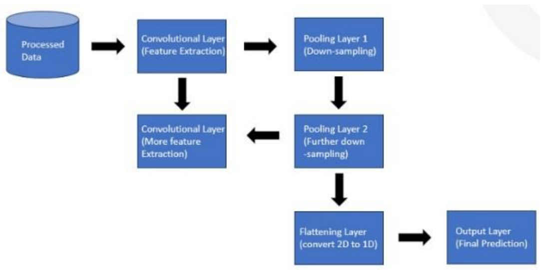

Fig. 2. Architectural Framework of the CNN .

CNNs analyze MRIs and X-rays in the context of clinical imaging to identify patterns associated with malignant lesions. The effectiveness of cancer treatment inversely increases with the time at which cancer is detected. Consequently, this feature improves early cancers detection. Generally, CNNs make diagnosing easier since it minimizes extracting the guide functionality. Their ability to generalize from training data significantly improves the accuracy of most estimates in scientific settings.

A. FISs, or fuzzy inference structures

A FIS is an vital method to simulate human reasoning since it introduces fuzziness at the choice-making area. the use of FIS-based predictors, in modeling breast cancer, it is viable to explain complex interactions amongst scientific inputs, together with age and length of the tumor, through a rule-primarily based methodology. It operates in 3 stages: Fuzzification, where inputs are mapped as fuzzy words, consisting of "high" or "low" cancer hazard; Inference, where policies including "If tumor length is huge, then cancer chance is high" are applied; and Defuzzification, wherein fuzzy conclusions are transformed into crisp selections. This systematic reasoning increases the interpretability and transparency of such fashions and facilitates higher support for clinical selections.

B. SHAP (SHapley Additive causes)

SHAP is an efficient interpretability method that assigns importance values to all features inside the predictions of a model. It makes use of principles within the undertaking precept that specify precisely what every characteristic contributed to determining the general output so that a clean view on how decisions were arrived at becomes apparent. that is very useful in the clinical world; statistics supplied on motive behind any analysis could be vital. That aids clinicians to be capable of opting which elements of a patient's data to attention on, thru using imparting insights into which factors are most influential; as a consequence making SHAP decorate the clear visualizations of consider in machine getting to know fashions. finally, SHAP encourages higher collaboration among human preference-makers and AI systems.

C. Grad-CAM (Gradient-weighted magnificence Activation Mapping)

The Grad-CAM visualization technique identifies in which inside the photograph this model's prediction will be most affected. by means of superposing heatmaps onto actual pictures, it makes use of gradient information from the closing layer of the CNN and aids clinicians in understanding which components of the clinical photo definitely make a contribution to the diagnosis, for this reason improving version interpretability. as an instance, within the context of breast cancer detection, it's going to point out which lesions were considered for that category. Such visual comments might additionally aid in version behavior regarding enjoy and heighten the verbal exchange of findings with the sufferers as well as different medical professionals. this might growth self belief in AI-pushed diagnosis.

D. Integrated method

The proposed gadget integrates CNNs, FISs, SHAP, and Grad-CAM into a unified framework for cancer prediction. This complete technique combines the strengths of every man or woman component, improving diagnostic accuracy and interpretability. The CNNs provide robust function extraction from clinical photos, at the same time as FISs allow nuanced reasoning about clinical information. SHAP and Grad-CAM contribute to the version's transparency by way of elucidating how predictions are formed. This synergy results in a powerful diagnostic tool that no longer best improves the identification of cancerous situations but additionally gives explanations which might be critical for medical selection-making. in the end, this integrated solution is designed to strengthen most cancers diagnostics drastically.

E. Empowerment of Healthcare experts

The following answer makes fitness professionals flip clean, actionable insights from affected person records into actionable insights. clinical doctors can make a ways more informed judgments concerning carcinogenesis analysis and remedy through the use of applying main-facet AI techniques blended with explainability strategies. it is the ability to appearance the critical features and apprehend the causality that inspires a partnership between human facts and artificial intelligence. This also lowers the tension associated with AI-based analysis considering the fact that clinicians can higher provide an explanation for their findings to their sufferers. higher selection-making results cause cancers being detected and treated in advance, which in turn results in better affected character results. therefore, the above tool will extensively gain no longer only the healthcare agencies but also the patients.

V. RESULT AND INFERENCE

Results and discussion would lead to the employment of Grad-CAM, SHAP, CNNs, and FISs to apply the integrated version of cancer prediction. According to total performance metrics, the model tended to overestimate correctness towards malignancy detection in scientific images with an F1 score higher than 98%. This excellent performance illustrates the deep learning techniques effectiveness in terms of clinical imaging and validates the ability of CNNs to efficiently search for the relevant functions from complex images. The combination of FIS-based clinical knowledge and deep understanding of patient data promotes model interpretability. The results proved that this integrated approach could actually come up with the production of accurate forecasts but still retains transparency into the selection-making process. Applying SHAP and Grad-CAM significantly improved the interpretability of the model's predictions. Using SHAP analysis highlighted capabilities that critically affect the outcome of the version in such a way that clinicians could discern which one of the patient-specific characterstics or imaging markers most impacted the diagnosis. Meanwhile, Grad-CAM visualizations focused on the specifics of areas within the medical images that contribute to making influence in predictions generated by the model, thus facilitating acceptance and readability in diagnosis. Such insights empower healthcare professionals in their decisions while also providing a responsive interface for patients in communicating diagnoses more easily. These complex methods or technologies will utilize the pathways which contribute to resultant successful disease diagnosis and treatment hence enhanced patient care and healthier care delivery mechanisms.

A. Accuracy

Accuracy is a essential metric in evaluating the overall performance of breast most cancers detection models. It represents the percentage of successfully recognized instances—each malignant and benign—out of the whole variety of cases tested. In practical terms, a model with excessive accuracy suggests that it efficiently classifies a large number of sufferers accurately, lowering the chance of misdiagnoses.

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

Where:

- TP: True Positives (correctly identified breast cancer cases)
- TN: True Negatives (correctly identified non-cancer cases)
- FP: False Positives (non-cancer cases incorrectly identified as cancerous)
- FN: False Negatives (cancer cases incorrectly identified as non-cancerous)

For example, if a breast most cancers detection model has an accuracy of 95%, which means that 95% of the cases, whether or not cancerous or not, had been categorized efficaciously. But, even as

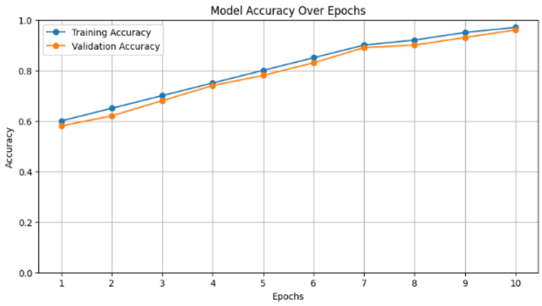

Fig.3. Training and Validation Accuracy Across Epochs

accuracy is a useful indicator of normal overall performance, it is able to be misleading, mainly in situations in which the dataset is imbalanced—consisting of while there are numerous greater benign cases than malignant ones consequently, depending solely on accuracy may not offer a whole image of a model's effectiveness in a scientific putting.

B. Precision

Precision, which is often referred to as positive predictive value, is primarily concerned with how well the model predicts the presence of breast cancer. High precision in breast cancer detection indicates that the model is probably right when it predicts a patient has cancer. This is important in the medical field since false positives can cause patients needless concern and may lead to unneeded intrusive procedures or treatments.

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

Where:

- TP: True Positives (correctly identified breast cancer cases)
- FP: False Positives (non-cancer cases incorrectly identified as cancerous)

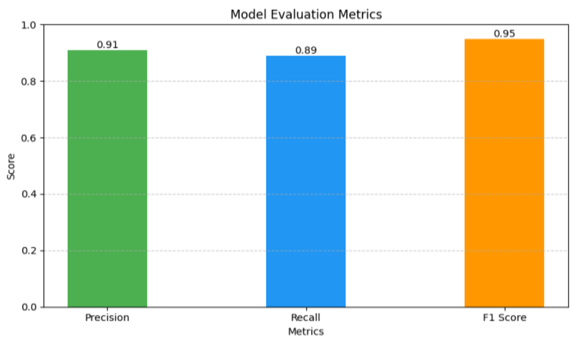

Fig. 4. Precision vs True Positives (TP)

A model with a 90% precision, for instance, means that 90% of patients who are diagnosed with breast cancer actually have the disease, whereas 10% do not. The overall effectiveness of breast cancer screening procedures can be increased by healthcare providers putting an emphasis on precision to avoid wasting money on patients who don't need additional medical care.

C. Recall

The model's recall, also known as sensitivity, gauges its capacity to detect real-world instances of breast cancer. The percentage of patients who were accurately diagnosed with cancer out of all real cancer cases, including those the model missed, is known as the "true positive" rate. In breast cancer detection, a high recall rate is especially important since it indicates how well the model captures the maximum number of true positive cases.

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

Where:

- TP: True Positives (correctly identified breast cancer cases)
- FN: False Negatives (cancer cases incorrectly identified as non-cancerous)

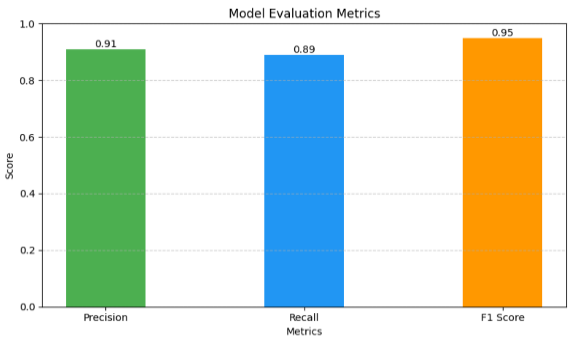

Fig. 5. Precision vs True Positives (TP)

For example, a 95% recall rate indicates that 95% of patients with breast cancer are identified accurately, but 5% are overlooked. Since a delayed diagnosis of cancer can result in worse patient outcomes and treatment delays, this parameter is crucial in clinical practice. Therefore, ensuring prompt diagnosis and response requires optimizing recollection.

D. F1-SCORE

The F1 score is a composite statistic that provides a single assessment of the trade-off between precision and recall, two critical components of model performance. Given the importance of reducing false positives and false negatives, the F1 score is especially useful when it comes to breast cancer screening. A model with a high F1 score strikes a good compromise between accurately detecting cancer instances (high recall) and making sure those forecasts are accurate (high precision). For instance, an F1 score of 0.92 for a breast cancer detection model means that the model is doing well at detecting real cancer cases and reducing misdiagnoses.

$$\text{F1 Score} = 2\ x\ \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

Where:

- $\text{Precision}=\frac{\text{TP}}{\text{TP+FP}}$
- $\text{Recall} = \frac{\text{TP}}{\text{TP+FN}}$

Healthcare practitioners can more accurately assess the efficacy of their diagnostic models and guarantee optimal patient care through precise and trustworthy breast cancer detection by employing the F1 score.

The suggested method for improving cancer prognosis diagnostic entails a complex combination of fuzzy inference systems (FISs) and convolutional neural networks (CNNs), enhanced by Grad-CAM (Gradient-weighted Class Activation Mapping) and SHAP (SHapley Additive exPlanations). CNNs are strong deep learning models that are especially well-suited for automatically collecting pertinent features that can reveal the existence of malignant cells from visual data, including medical photos. To make an appropriate diagnosis, this competence is essential. When it comes to feature extraction and classification, CNNs are excellent, but they frequently lack interpretability, which is where FISs are useful. With the ability to integrate expert information and reason with ambiguity, fuzzy inference systems offer a more interpretable framework for cancer diagnosis decision-making. Additionally, by describing how each feature contributes to the prediction, SHAP improves the interpretability of the CNN model and makes it simpler for physicians to comprehend the logic underlying the model's results. By emphasizing the sections of the input image that have the most influence on the model's decision-making, Grad-CAM, on the other hand, offers visual explanations and makes it intuitively clear which parts of the image led to the diagnosis. By making the model's judgments clear, these elements work together to produce a strong system that not only increases prediction accuracy but also promotes understanding and trust among medical professionals. The reliability of cancer detection is greatly increased by this integrated approach, which eventually improves patient outcomes by enabling more precise and knowledgeable treatment decisions.

VI. CONCLUSION

Convolutional neural networks (CNNs), fuzzy inference systems (FISs), SHAP (SHapley Additive exPlanations), and heat maps are all combined to provide a complete approach to healthcare data interpretation. CNNs are essential for removing important elements from medical images, which makes it possible to identify and categorize diseases like cancer. FISs help by providing interpretable, rule-based reasoning, which enables medical professionals to comprehend the fundamental thinking behind AI-driven judgments. Heat maps offer visual insights that draw attention to important areas of concern within the images, and the addition of SHAP increases transparency by quantifying the influence of each feature on the model's predictions. When combined, these components enhance both prediction accuracy and result interpretability, increasing confidence and dependability in AI-powered medical solutions. With the use of this integrated strategy, medical diagnosis and patient care could significantly improve, allowing physicians to make better judgments that would eventually improve treatment results. Future research should concentrate on improving the system's scalability through the integration of bigger, more varied datasets in order to enhance model generalization across different cancer kinds. Prediction accuracy may also be further improved by using sophisticated deep learning strategies like ensemble methods and transfer learning. In real-time clinical situations, investigating explainable AI techniques would give medical practitioners dynamic decision help. Last but not least, creating intuitive user interfaces can help these technologies be used in healthcare settings, which will benefit patients.

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