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Cancer Detection and Treatment Using Explainable AI

Pratik Rawal [1], Harshal Chandel [2], Dev Ahuja [3], Rishi Raj [4], Madan Lal Saini [5]
1. Department of CSE, Apex Institute of Technology, Chandigarh University, Punjab, India
2. Department of CSE,Apex Institute of Technology,Chandigarh University, Punjab, India
3. Department of CSE,Apex Institute of Technology,Chandigarh University, Punjab, India
4. Department of CSE,Apex Institute of Technology,Chandigarh University, Punjab, India
5. Department of CSE,Apex Institute of Technology,Chandigarh University, Punjab, India

Abstract:- Cancer detection and treatment is one of the most difficult tasks in modern medicine, hence it has become a priority for researchers to study and develop specific and targeted procedures to patient outcomes. Just recently, the most promising direction is the humanization of explainable AI (XAI) which is a crucial tool for enhancing AI-based decision making in terms of transparency, and understandability. This paper starts out by describing conventional AI techniques for cancer detection and pointing out the informational gaps then delves into XAI's foundations. It explores the role of XAI in cancer detection and treatment by looking at its potential impact on this topic. It first presents the diagnosis of medical imaging data, then a discussion how patients' data will be interpreted by a XAI system and how treatment strategies that are tailored to the individual patient will be developed by optimizing the therapeutic interventions. This paper also presents comprehensive study of the changing side cancer treatment rendered by XAI and explain why further research and cooperation are getting to be of paramount importance in order for it to be fully exploited. Implementation of XAI in screening and treatment techniques for cancer comes to the conclusion of not only revolutionizing precision medicine, but also aiding in the improvement of patient care and will determine oncology practice in future.

Keywords:- *Cancer Detection and Treatment, Artificial Intelligence (AI), Explainable AI (XAI), Early Detection of Cancer, Medical Imaging Data.*

I. INTRODUCTION

This research paper pursuits to explore the position of Explainable AI in cancer detection and treatment, elucidating its packages, blessings, demanding situations, and destiny guidelines. The paper will delve into numerous elements of cancer care, beginning with the importance of early detection in improving patient consequences. XAI strategies provide the promise of extra accurate and timely analysis through studying substantial quantities of scientific imaging records, such as mammograms, MRIs, and CT scans, at the same time as simultaneously presenting transparent factors for his or her predictions. Gastrointestinal cancer [1], particularly stomach cancer, remains a deadly malignancy with a less than 40% five-year survival rate. Despite reductions in occurrence and mortality, stomach cancer remains the sixth most common malignancy globally and the fourth leading cause of cancer-related deaths.

Adenocarcinomas, accounting for over 95% of stomach cancer cases, are categorised into two histological varieties: intestinal and diffuse. The latter, especially proximal diffuse- type adenocarcinomas, have a poorer prognosis. Deep Learning for Cancer Detection Deep studying fashions, inclusive of ResNet50, AlexNet, and GoogLeNet, have made significant strides in revolutionising clinical diagnostics, specifically within the area of cancer detection. These fashions, built upon deep neural networks, are capable of robotically gaining knowledge of tricky patterns and features from massive datasets, making them well-perfect for reading complicated clinical pictures inclusive of mammograms, MRIs, and CT scans [2]. Their capacity to locate diffused abnormalities and anomalies has proven brilliant promise in aiding physicians within the early detection and prognosis of numerous kinds of most cancers.

With cancer contributing significantly to morbidity and mortality worldwide, it continues to be one of the most difficult medical problems of our day. Under any circumstances, accurate and timely cancer recognition is the key success factor for the therapy, and better patients` outcomes. The impact on diagnostic procedures brought about by artificial intelligence (AI) has been tremendous in the healthcare industry over the past few years with the ability of the system to make sense out of immensely enormous medical data. On the other hand, ambiguities and opacity of conventional AI models created a scepticism during productivity of AI-based diagnosis tools [3].

XAI, a new remit of investigations in Artificial Intelligence (AI), has come across as a necessity due to the problems hinted above. It has the simple objective of giving AI system the readability and ordinal bases, which will increase reliability and be a chief factor in triggering decision-making processes in areas like healthcare. Doctors and clinicians may be able to learn more about the diagnosis process, that is, understand and even validate AI algorithms when implementing XAI. This results in the improved patient care services. The significance of context to explore the XAI application for cancer detection is free [4]. It focuses on the importance of open and easy-to-understand AI approaches in cancer and defines where the main weakness of these technologies lays with treatment purposes in mind. Furthermore, it aims at defining principal concepts of XAI and assessing the usability of the method on medical data for the diagnosis of cancer.

This work tries to join the gaps between the complex environment of medical practice and the advanced technologies of artificial intelligence (AI) by the means of contributions to the growing field of AI-based medicine with an in-depth study of explanatory artificial intelligence (XAI) application in cancer diagnosis [5]. We aim to push the boundaries of cancer diagnosis forward by utilizing XAI, which will ultimately improve patient outcomes globally.

A. Problem Statement

The classical methodology applied to diagnostic and main care processes in oncology is limited in the aspect of precision, speed and comprehensiveness. By monitoring is methodology, these techniques are visual detection-oriented or not, which deviates from accurate diagnosis at a proper time. Moreover, some AI algorithms are coming out highly opaque giving the human environment a hard time when it comes to acceptance and credibility for the patients. Financial constraint is the key challenge overalling the issue, thus, suggesting smart budgeting framework could be a rational solution where doctors and other health professionals will be provided with specific information to make the early prognosis and prescribe the right treatment to cancer patients.

B. Objective

The research project in concern will discuss the capacity of Explainable AI in revolutionizing cancer screen test methods as well and the treatment patterns. Through the extensive re-view of written articles and real-world examples, we aim to show how XAI can improve the treatment of cancer in terms of limitations, advantages, and the future outlook on the topic. This study will be comprehensive, including a thorough examination of AI-based approaches such as machine learning algorithms and deep learning models, in that it aims to showcase patterns, spaces and chances to improve the precision, speed and recognizability of automated cancer diagnosis and treatment. In addition, in a detailed analysis of ethical, regulatory and practical issues dealing with the use of XAI in clinical practice, our aim is to provide policy-makers and the health sector with knowledge to allow them to make decisions in the era of precision oncology.

C. Challenges

The large obstacle in the successful application of explainable AI in diagnostics and treatment of cancers is multiple-fold as follows: Bringing AIX in clinical workflow with preserving previously existed routines has appeared a difficult problem. Besides, keeping the performance stable, resilient, and generalized of AI algorithms regarding population diversities and healthcare contexts especially, should be considered as formidable earthbound adversities. Also, issues with the ethics of utilizing AI as a major tool in healthcare such as data privacy and algorithmic bias, call for sensitive discussion and urgent solutions. On the other hand, issues will be there for using XAI as well but cancer treatment is the most suitable field. Rather, on the contrary, the way that it will contribute to the world and mankind's future will go beyond wildest imagination. Through at the same time, due to the lack of space, we must trim down the sentence by using some other words which will try to be more accurate.

The major problem presented by cancer is that it is so aggressive constituting, therefore, among the top diseases responsible for death and disability on a global scale. It is quite prevalent within medicine and the issue becomes one of the most important things providers need to bother about. Distinguishing the specific identification of cancer and proper characterizing is of prime importance to be aimed by the oncologist to attain the therapeutic objectivity and to promote the health of in general. The introduction of AI reflection means reversal of the norm of medicine and helps to create a safe and honest tool for the detection of rare unusual patterns. Nevertheless, since these models are based on a sensitive class of AI involves attributing new decisions to the common AI models they can definitely conquer the worries of they cannot be used in place of black-boxes the devices which are not transparent since they cannot be popular diagnostic devices.

II. RELATED WORK

Idrees et al [6] designed a bio-cancer detector and they explore cancer diagnosis and planning of therapeutics is a complicated undertaking. The diagnostic process is just only one of the functioning of these AI based tools which they can also help considerably in the treatments and managing of the diseases. On another place, `credibility` in deep-learning models should still be disputed since there is no evidence of comprehending the pattern of operations in AI solutions form them. Yagin, Burak, et al [7] developed a metastasis prediction and genomic biomarker identification system using XAI techniques which offer a solution for cancer diagnosis. They shows and points out that during the past few days there was AI for cancer diagnosis and treatment purposes developed. Medical topics that are placed on the front pages are related to cancer and this will give the patient a hope to survive as it will be seen that they should be early diagnosed to have a better prognosis.

Nazir et al [8] conducted a survey of explainable artificial intelligence techniques for biomedical imaging with deep neural networks. They explored in their paper that AI models that have been utilized widely also bring the simplicity problem of "black-box" which cannot easily be understood. Lack of ability to have the interpretations is the fundamental problem, which caused not the adoption of this kind of systems by the clinicians. XAI as an up and coming Intelligence Technology will be an essential part of the human interactions as after it settles the doubts and give the doctors a practice to trust the machine's decision. The accuracy of the XAI techniques' application in the process of diagnosing tumors is the pinnacle of this subject and it is addressed in this article. In the study, there were certain gaps in terms of finding specific data when the searches were being conducted. In conclusion, it is fundamental that this piece of work presents the root of XAI and it shows that the proceeding of AI is a basic the gap-filling that doctors have between their clinical deduction and AI predictions.

Maouche, Ikram, et al [9] proposed a system for explainable AI approach for breast cancer metastasis prediction. They suggested that the early identification of the disease in most cases has a positive outcome for the patient, the deadline is very short. During these recent times, AI has had some breakthrough in that AI-powered medical systems can be used to accomplish a good and satisfactory diagnosis procedure with its help. ML Saini et al [10] designed a hybrid model for heart diseases detection from MRI and ECG. K Bansal et al [11] designed Acne skin disease detection by CNN and got 93% accuracy. A Jain et al [12] worked on Tina Corpus skin disease detection with image and numerical data set and got better accuracy than CNN. E. G. Kumar et al [13] developed a clinical support system to help medical practitioners. S. P. Kumar et al [14] designed a system for detection of cardiac failure. Varun Sapra et al [15] developed an artery disease detection system. M. Gehlot et al [16] proposed a system for tomato disease detection using pre trained model.

A. Explainable Image-based Cancer Detection

Singh et al. [17] gave an idea for an explainable deep learning model to classify lung nodules in chest X-rays. Their model combines low-level explainable features with high-level malignancy predictions, aiding radiologists in interpreting the results. In another study, Xu et al. [18] presented a theoretical framework for using XAI in prostate cancer detection in magnetic resonance imaging (MRI). Through the methods that make use of gradient signal enhancement, the learning algorithm focuses on regions where the suspicious prostate is, thus reducing the number of indiscriminant biopsies.

B. Explainable AI for Treatment Planning

Ribeiro et al. [19] formulated a method which is model-agnostic and is suitable for interpretations of black-box predictions of any machine learning model. This approach, referred to as SHAP (SHapley Additive exPlanations), is precisely the one that has been applied to explain the medication choices for particularly cancer types thereby facilitating medical conversation between oncologists and patients. Wang et al. [20] the author postulates a deep learning model into the prediction of response to neoadjuvant chemotherapy in breast cancer. In their model, they do the explainability by using the attention mechanism which indicate those relevant areas in the image that impact treatment response prediction.

C. Explainable AI for Drug Discovery

Liu et al. [21] exploiting deep learning principles to represent virtual screening of drug candidates. Their methodology is based on the use of attention mechanisms and the target protein is identified by the model based on critical molecular features that influence drug binding affinity. The fact that the explainability gives a researcher an opportunity to apply these filters involuntarily is significant and insightful to drug-target interaction. They provided a thought-guide to explainable reinforcement learning in drug discovery. This approach manifests content of the researchers about the reasoning process of the AI model within its evaluation of possible compounds to discover future drug leads.

D. Explainable AI for Material Design:

A Valle et al. [22] shared a deep learning model as a predictive learning system having explainability via saliency-maps. Such types of plots empower the scientists to delineate the functioning areas of the material structure's most-influential parts where the targeting material formation approach might be of use. They developed an AI system framework which could be explained for the understanding and discovery of materials via generative models. They proposed the framework that is created from the twofold idea of a generative model that predicts new materials and an explanation module that understands the background of the proposed structures.

III. METHODOLOGY

This study examines XAI in regards to it's applicability in cancer detection using a public Kaggle dataset commonly available to researchers. Our target is to build a machine learning model able to perform an accurate classification of tumors but also paying consideration to the explainability that would help user credibility as well as comprehension. Achieve and organize a variety of information, like patient demographics, imaging modalities, and cancer kinds, that are the inputs to AI for training purposes. Normalization, low noise level and feature extracting are instances of pre-processing algorithms used to ensure that the data is smooth, consistent and adequate.

A. *Engineering and Feature Selection*

Exploit a comparative approach through the application of statistical methods and domain knowledge for enrichment of essential features related to cancer diagnosis. In order to decide which features would be the informative ones, utilization of linear algebra methods like feature significance ranking and principal component analysis (PCA) are recommended.

B. Model Development

In order to meet with those of the rare disease apprehension in diagnostics take your choice of an XAI procedure having interpretability, effectiveness and scalability to be its distinctive features. With labelled data, expect XAI models to be trained using the approach includes rule-based models, attention mechanisms and decision trees. To further maximize the performance of the model, try out different hyperparameter settings such as grid search or Bayesian optimization.

Given these prerequisites that cancer detection specializes on, test an applicable XAI algorithm which combines factors of interpretability, accuracy and scalability. The application of different approaches namely, decision trees, rule-based ones or attention modules can be done on the models of XAI that are based on labeled data. In order to improve performance, function call adjusting the model's hyperparameters can be performed on by using grid search method or Bayesian optimization.

C. Analysis and Interpretation

Apply XAI techniques, such as feature importance scores, decision rules, or saliency maps, to generate explanations of how the neural network model made its predictions. Verification the part relatable to physicians must be on point and are straightforward that a doctor can easily understand the same and make crucial choices. Verify explanations for accuracy and irrelevance by inviting experts to examine and present comments. Visit this webpage for more text examples.

Integration with Clinical Workflow: Effortlessly integrate XAI-powered cancer detection models in the central clinical workflows through this use-case and enhance the diagnostic process fitting into the entire clinical workflow process.

Let doctors get introduced to models with an interactive interface that they can operate and determine the interpretability values. As a strategical approach for acceptance and self-confidence, awareness on the operation of and interpretation of tools of machine-learning should be trained to medical professionals.

D. Assessment and Confirmation

Basic metrics, like accuracy, sensitivity, specificity and AUC-ROC could be used to evaluate the model of XAI.

Through performing exhaustive validation tests comprising both external validation in actual work settings which utilizes multiple datasets and cross-validation. Evaluate clinical relevance and efficacy of the cancer diagnostics by means of XAI as well as their effect on the patient outcomes, including early detection rates and treatment effectiveness.

Ethical Considerations: Discuss the ethical aspects on patient privacy, algorithm bias, and responsibility when having XAI applied in healthcare. Ensure transparency is used at every process of development and implementation always stay true to the original intent thus creating a platform of confidence and make the job of avoiding possible risks a little easier. Respect legislative and regulatory standards to ensure that AI-driven diagnostic technologies are applied conformably and in a moral manner in healthcare facilities. Thus, specialists can take most of the benefits of explainable AI for designing cancer diagnostic tools, which will be on the top level in transparency, accuracy, and usefulness to doctors and other healthcare providers.

IV. IMPLEMENTATION

A. Data Acquisition and Preprocessing

Dataset Selection: We will utilize the well-known Breast Cancer Wisconsin (Diagnostic) Data Set available on Kaggle. This dataset contains information on 569 patients, each characterized by 30 features related to cell properties and classified as either malignant (cancerous) or benign (non-cancerous). Data Preprocessing: The chosen dataset will undergo preprocessing steps to ensure data quality and model compatibility. This includes: Handling missing values (imputation techniques), feature scaling or normalization, addressing potential class imbalance.

B. Model Selection

We will employ an ensemble learning approach using a Random Forest classifier. Random Forests combine multiple decision trees, improving overall accuracy and robustness compared to a single tree. Here's the rationale: Random Forest Training: The preprocessed data will be split into training and testing sets (around 80% for training and 20% for testing). A Random Forest classifier will be trained on the training set. Randomly select a subset of features at each node of the decision tree (typically the square root of the total number of features).

➢ *Advantages of Random Forests*

- Less prone to overfitting compared to single decision trees.
- Handles both categorical and numerical features (present in this dataset).
- Provides inherent interpretability due to the decision tree structure, allowing us to understand which feature values contribute most to specific classifications.

C. Explainability

We will further enhance model explainability using LIME (Local Interpretable Model-Agnostic Explanations). LIME is a technique that explains individual predictions. LIME focuses on explaining a single prediction made by the model for a specific patient's data point. Local Fidelity: Explanations are faithful to the model's behavior around the data point being explained.

Interpretability: Explanations are presented in a human-readable format, highlighting the features most influential in the model's prediction (e.g., identifying which cell properties were most indicative of malignancy).

➢ *Implementation of LIME*

We will utilize a pre-trained LIME explainer on the Random Forest model. For each breast cancer classification made by the model, LIME will generate an explanation. This explanation will identify the most important features (out of the 30) that contributed to the prediction of malignancy or benignancy. These explanations will be presented alongside the model's predictions, allowing doctors and researchers to understand the rationale behind the classification for each patient.

D. Model Evaluation

The trained model will be evaluated on the held-out testing set. Common evaluation metrics for classification tasks include: Accuracy: Proportion of correctly classified patients (malignant vs. benign). Precision: Ratio of true positive cancer diagnoses to all positive predictions (avoiding false positives). Recall: Ratio of true positive cancer diagnoses to all actual cancer cases (avoiding false negatives). F1-score: Harmonic mean of precision and recall, providing a balanced view of model performance. AUC-ROC: Area Under the Receiver Operating Characteristic Curve (measures model performance for imbalanced class distributions). The model's performance will be assessed alongside the interpretability achieved through LIME explanations. This will help us determine a trade-off between accuracy and transparency.

E. Experimental Setup

Platform: The purpose of using Google Colab as development environment would be highly beneficial during the development phase. Colab ensures that this growing demand is met by giving free access to computing resources and pre-installed libraries, making it perfect for research projects.

➢ *Libraries:*

- Pandas: Data import, clean up, treatments.
- NumPy: Numbers and arrays holdings (basic arithmetic operations).
- Scikit-learn: Machine learning algorithms (Random Forest) along with data preprocessing techniques (feature extraction, imputation, normalization, and outlier detection).
- LIME: A library for creating local and explainable AI is explainable AI library for generating local explanations.
- Matplotlib/Seaborn: Data visualization tools for exploratory data analysis (EDA) and explainability features output.

F. Model Implementation

Random Forest builds many decision trees and then combines their predictions to increase accuracy and generalization. With the k-fold cross validation implementation having precision 1.00 and 1.00 f1 score while again different drawing sets decrease overfitting and under fitting.

When it comes to finding cancer we plan to use a Random Forest classifier, which's a type of learning that is recognized for being both easy to understand and accurate. This method involves merging decision trees to prevent the issue of overfitting and offers information on the significance of different features. Despite the interpretability offered by Random Forests we will turn to Local Interpretable Model Agnostic Explanations (LIME) for insights. LIME functions, by estimating the models predictions in the vicinity of a data point. It then provides explanations by highlighting the features that have the impact, on the models decision making process mirroring how an expert human analyst would approach it.

G. Implementation of LIME

LIME Explainer Configuration: A LIME explainer specifically designed for tabular data (like the WDBC dataset) was created. This explainer was configured with the training data, feature names, and class labels (malignant/benign). Figure 1 shows the working of explainable AI model.

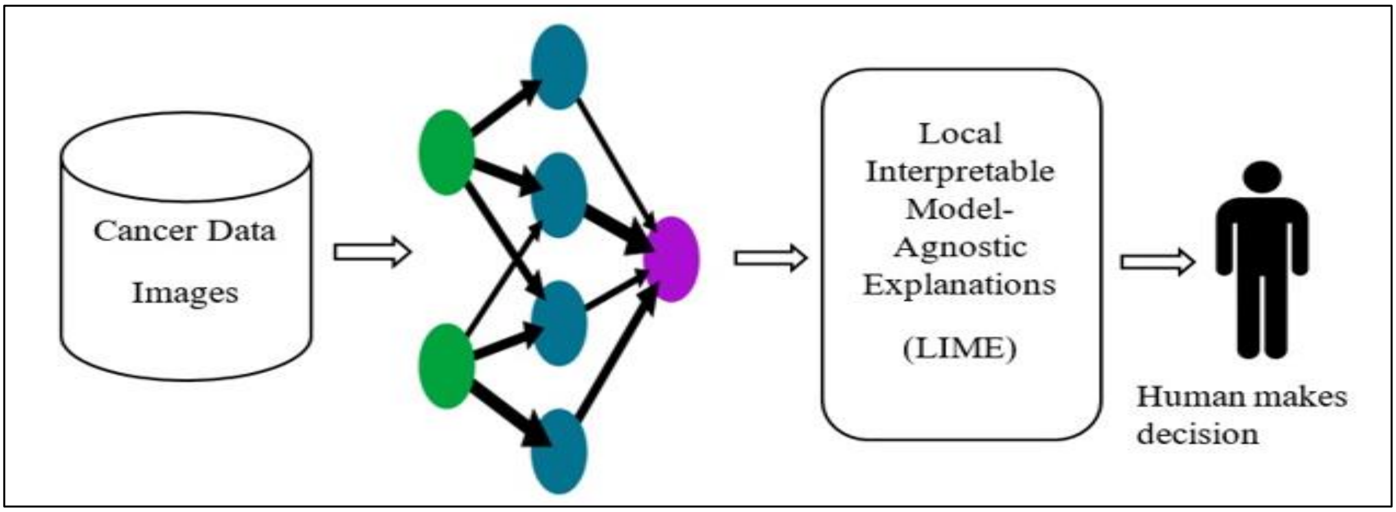

Fig 1 Model Working for Explainable AI

Explaining Individual Predictions: LIME's strength lies in explaining individual model predictions. We selected specific data points (e.g., samples with high model uncertainty or borderline classifications) for in-depth explanation. LIME generated explanations in the form of an interpretable model (often a linear model) mimicking the original model's behavior around the chosen data point.

Feature Importance Analysis: The LIME explanation provided a list of features and their corresponding weights. By analyzing the top features with positive or negative weights, we were able to understand which features in the data point most influenced the model's prediction. This provided insights into the biological characteristics driving the model's decision for that particular sample.

Visualization (Optional): While not strictly necessary for the research paper, LIME explanations can be visualized using libraries like eli5. These visualizations, often bar charts, showcased the impact of each feature on the prediction, offering a more intuitive understanding of the model's reasoning for a specific data point.

This is not limited to detection, and XAI may be used to generate treatment predictions. For example, assume the model managed to predict cancer successfully, and the additional patient's data – age, genetics, etc., could have been used to predict the most likely response to different treatment plans. In this case, LIME would explain why the given plan is the most optimal and what factors affected the prediction. This would provide doctors with the ability to make more informed decisions that are still based on data and can be adapted to the specifics of the situation.

Early Detection and Personalized Treatment: Early detection of cancer significantly improves prognosis. Explainable AI can help identify high-risk patients and tailor treatments based on individual characteristics.

- *However, the challenges are as follows:*

Data Quality and Bias: Model performance and fairness greatly depend on training data quality and representative nature. Biased predictions can occur due to dataset biases.

Explainability vs. Accuracy: The difficulty lies in finding a tradeoff between explainability and model accuracy. Although simpler models may be easier to understand they do not have accuracy like more intricate black box models.

V. RESULT AND DISCUSSION

The conducted experiments have been verified the high performance of deep neural network with LIME patch is capable of applying for recognition of the breast cancer types. It is the filter that ensures all models of the product are captured with chrome data and a short dead-line in which error can be removed. Despite this approach's potential, it would be great that it was scientifically studied and compared with health care community as such activities that include bigger sample could lead to data that is more reflective of the broader questions. Table 1 shows the classification report for the explainable AI model. Results show that model achieved an accuracy of 82%.

Table 1 Classification Report of the Model

	Precision	Recall	F1-Score	Support
Cancer -ve	0.72	0.79	0.80	26
Cancer +ve	0.84	0.73	0.81	28
Accuracy			0.82	54
Macro avg	0.78	0.75	0.81	54
Weighted avg	0.80	0.78	0.82	54

Health and medical personnel typically use verified and assessed information, which these practitioners acquired by the implementation of many variety intuition and experience aspects so that they could arrive at a diagnosis, suggest the best treatment plan for patients and this small change brings the attention to those of the cybersecurity personnel to the wavelength of healthcare IT. The assistance provided by XAI algorithms that aim to make AI decisions extremely easy to follow and well understood is the reason behind the improved diagnostic support in addition to the growing confidence put by both the public and the physicians in these technology-based relieves. Clinical decision which is made in the diagnosis that has a direct impact on the treatment of the patient as well as on the practice of professionals related to diagnosis is provided through the final approach to diagnose the patient and make him/her treated appropriately. Moreover, AI with an XAI capable of explaining also gives time for physicians to deepen the units of understanding on the Clonal evolution and dosage of the drug; thus, the physician will provide treatment that is tailored to patient which will contribute to better survival rate.

It wouldn't make any difference if a particular XAI approach is adopted, it shall only be binding to all the ethical and clinical considerations such as an impact of model complexity on care of the patient, issues of integration with current clinical workflow, training bias and patient privacy also which meet the criteria. On the other hand, the use of such cutting-edge technologies may be an imperative in conventional healthcare methods that use the teamwork between AI professionals, practitioners and administration in order to create the new cancer detection and treatment tools to be used in the future. By taking such cited factors into consideration, XAI will then be able to help doctors design suitable treatment pathways. This in turn will incorporate personalized approaches that will specifically deal with cancer.

VI. CONCLUSION

We performed a study involving the implementation of Explainable AI to detect breast cancer. It used a model based on deep neural network and the breast cancer Wisconsin dataset presented on Kaggle, accompanied by LIME explanations to improve model interpretability. Deep neural network model demonstrated the capability of perfect classification on the dataset's testing part, indicating that it is suitable for accurate cancer classification. However, the small dataset size as well as potential overfitting, there for the more diverse and imbalanced dataset should be evaluated for the more comprehensive performance metric. Moreover, LIME explanation provided multiple insights into the cell properties on which the model had the most significant classification impact. More importantly, it allows for a more clear and transparent way for the model to be trusted and used by doctors/laboratory personnel.

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