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Resolvable Artificial Intelligence Method in Smart Healthcare

Abstract: - Autonomous vehicles, social networking and online store recommender systems, financial technology, question answering systems, and natural language processing are just a few areas that have made extensive use of Machine Learning (ML) algorithms. Since its inception fifty years ago, the rule-based approach to illness diagnosis and clinical decision support has garnered considerable attention. This strategy is focused on curating medical information and building powerful decision rules. Predictive modeling in healthcare has recently shown promise for ML algorithms that can account for complicated connections between features. Despite the impressive effectiveness of many ML algorithms, their lack of explainability makes them difficult to fully use in real-world clinical settings. Explainable artificial intelligence (XAI) is developing to help people explain their inner thoughts, feelings, and behaviors to medical experts. The ability to understand how to use predictive modeling in real-life situations somewhat objective carelessly resulting the predictions is a key component of XAI's success in gaining physicians' confidence. Because medical knowledge is complicated, there are still numerous possibilities to investigate in order to bring XAI to a clinical context where it may be effective.

Keywords: XAI, ML algorithms, Artificial Intelligence (AI), Dataset, Classifier.

I. INTRODUCTION

Sustainability must be at the forefront of every service that the next generation of Smart cities wants to provide (Singh, Sharma et al., 2020). There are a wide variety of possible expressions of sustainability. To reach the goal of healthcare service sustainability, several approaches and mediums may be used [1]. Intelligent gadgets can now accomplish tasks including interpretation, self-monitoring, diagnosis as well as AI analysis, which is a key factor propelling the industrial revolution. AI methods, especially those based on ML and Deep Learning (DL), may help manufacturers and other companies reduce downtime by predicting when they will require maintenance [2]. The healthcare industry is rapidly embracing AI for a variety of purposes, including patient data and diagnostics, health services administration, clinical decision-making, and predictive medicine.

As enigmatic beings, people are wary of using AI models, even if they may be just as capable as humans. This mistrust is still the main reason they aren't more widely used, especially in healthcare [3]. Recent advances in AI have the potential to aid doctors in making choices that reduce mortality and illness. Still, the interpretations of the results are a typical weakness of many modern studies. The user does not have access to the complex logic that goes into making the predictions [4]. Within the European Commission-funded project context [5], including a smart city flood monitoring app, this study proposes a method based on Semantic Web technologies to the "XAI" issue and the idea of "explainable DL"(XDL) as a subset of that challenge. Data derived from a variety of studies that have investigated XAI in theory and practice [6]. This would help researchers understand the current trends in XAI and maybe direct future research toward the development of domain- and application-specific methods.

Following this conceptual study, an ethical examination was conducted to determine whether medical AI requires explainability. The framework used for this evaluation was the "Principles of Biomedical Ethics" proposed by Beauchamp as well as Childress, which include beneficence, autonomy, nonmaleficence along with justice [7]. These days, AI is all the rage, and with good reason: it has the potential to revolutionize several industries, including healthcare. But for the better part of a decade or two, AI has been treated as a black-box model insight into how it really operates. The building blocks of many AI systems are weights, which are obtained via large-scale matrix multiplications. In most cases, the computationally intensive processes are not easy to comprehend or fix [8].

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Unfortunately, ML inability to be explained to decision-makers limits its widespread use in healthcare applications, where understanding the underlying reasoning is crucial. The potential downsides of AI's inability to explain itself in the healthcare sector might balance its potential aids of accuracy, speed as well as decision-making effectiveness.

- This work, examine a number of application cases and examples of XAI techniques applied to the heart disease dataset from UCI.
- The goal of this paper is to examine and apply various XAI techniques to healthcare.
- These techniques provide a foundation for trust, transparency, consistency, and fairness in the system.
- Based on the results, the research chooses a method over another for a specific healthcare area especially heart in this research. This research also has developed a number of techniques that explain the results.

The rest of this work is planned as surveys. Section II gives an outline of some current and recent works. The proposed technique is defined in Section III. After a summary of the findings as well as analysis in Section IV, the references are provided.

II. Recent Works For Research

This part, look back at some of the more recent articles written on ML techniques. Table 1 summarizes the Suggested ML techniques for development and lists their advantages and disadvantages, to find all the information needed

Table I: Literature review

Paper and Author	Method	Advantages	Limitation
Ahmed et al. [9]	Internet of Health Things (IoHT) and AI	ensure accuracy across the healthcare infrastructure	Medical data used to train the MLmodel, were not well explained, despite the expectations of both academics and healthcare practitioners.
Whig et al. [10]	Explainable ML (XML)	increase the dependability of an incorrect prediction	The ability to accept the logic behind the predictions made by ML models is crucial for doctors who want to begin cancer treatment based on diagnostic predictions
Hassan et al. [11]	DL techniques	Improved accuracy	To build a fusion model using the dataset's top feature extractor model for classification
Tiddi et al. [16]	XML	very accurate results	The capacity of XAI to circumvent the problems with modern ML systems has made it a hot topic recently.

Table 1 details several novel techniques. Present methods include a suggested techniques, including AI XML, Blackbox models as well as DL techniques.These technologies provide a advantages, including improved accuracy , increasing tendency towards developing medical XAI systems.Nevertheless, other downsides, such as the inexpensive real-time prognostic system, are also brought up.

Ahmed et al. [9] defined the AI as "the ability of a machine to do actions that resemble judgments made by human intellect," is discussed. The Internet of Health Things (IoHT) and AI have revolutionized the medical industry, respectively. Unfortunately, the system's predictions, which were based on the medical data employed to train the ML model, were not well explained, despite the expectations of both academics and healthcare practitioners. Therefore, researchers have delved into the concept of XAI to ensure accuracy across the healthcare infrastructure and provide an explanation for the machine predictions. Because it is wrong to put one's faith in the machine's decisions to save a soul without fully understanding the reasoning behind them.

Whig et al. [10], discuss the medical diagnosis is one of the many uses of ML in healthcare. Wisconsin Breast Cancer Diagnosis (WBCD) is a popular dataset among cancer researchers. ML models in healthcare, as in other industries, remain mostly unexplored. The ability to accept the logic behind the predictions made by ML models is crucial for doctors who want to begin cancer treatment based on diagnostic predictions. Expert doctors in a particular field may use this knowledge to spot mistakes in ML models' predictions. To do this, a variety of methods are available. Among the methods is "XML." This project aims to increase the dependability of an incorrect prediction by developing XML using the WBCD dataset.

Hassan et al. [11] developed an automated classification system for detecting prostate cancer in MRI and ultrasound images using a combination of DL techniques. On top of that, the proposed scheme clarifies why a certain choice was taken using the input MRI or US image. Numerous pre-trained DL models with custom-built layers are superimposed into the datasets on the matching pre-trained models' top. With the best model, we can get 80% accuracy on the MRI images from the test set and 97% accuracy on the US images. The second step was to build a fusion model using the dataset's top feature extractor model for classification.

Knapic et al. [12] highlight the decision support in medical image analysis environments was offered using XAI techniques. To improve the explainability of the Convolutional Neural Network's (CNN) decisions by applying three distinct CNN techniques to a single set of medical imaging data. In an attempt to increase healthcare providers' trust in black-box predictions, visual clarifications were given to in vivo gastral photos got by a video capsule endoscopy (VCE). In addition to two post hoc interpretable ML techniques, SHapley Additive exPlanations (SHAP) as well as Local Interpretable Model-Agnostic Explanations (LIME), it used the Contextual Importance along with Utility (CIU) method as an alternate explanation strategy.

Kuzlu et al., [13] described the several smart grid applications have used AI techniques over the last two decades, including predictive maintenance, demand response, along with load forecasting. When it comes to complicated systems like solar photovoltaic (PV) projects, AI is still a "black-box" as of its inexplicability and opaqueness. A new subfield of smart grid technology, XAI addresses this knowledge gap by elucidating the logic underlying the AI system's predictions. This article grants use examples of solar PV energy predictions that use tools like SHAP, ELI5, and LIME.

Islam et al. [14] detailed the Electroencephalography (EEG) may be utilized for neurologic prognosis, post-stroke treatment, acute stroke prediction, and as a predictive method for providing cortical dysfunction after an ischemic stroke. Uses ML models to order the ischemic stroke group along with the healthy control group in order to forecast the occurrence of acute stroke in active settings. Also, XAI tools (Eli5 as well as LIME) were used to describe the model's behavior and identify the main components of stroke prediction models. A total of 125 healthy adults and 48 hospitalized patients with acute ischemic strokes participated in the research. We obtained the EEG three months after the patient first showed signs of an ischemic stroke.

Srinivasu et al. [15] discussed many sectors have automated decision-making with the use of AI models. This includes healthcare and commerce, two of the most important fields because of their direct influence on people's lives. Even though most AI systems are seen as opaque black box models without explainability, there is an growing tendency towards developing medical XAI systems using attention processes and surrogate models. An AI system is deemed explainable if humans can comprehend its decision-making process. Several healthcare initiatives that are driven by XAI are discussed here. Various explainability tactics pertaining to rationality, data, and performance are covered in this work, along with the toolkits used for local as well as global post hoc explainability.

Tiddi et al. [16] provided Knowledge graph applications in XML. The capacity of XAI to circumvent the problems with modern ML systems has made it a hot topic recently. These systems often provide very accurate results that are hard to comprehend and understand. Many are beginning to wonder if it would be possible to build a new kind of hybrid intelligent system by combining knowledge representation methods with ML application. This is mostly due to the fact that the two techniques have complementary strengths and weaknesses.

III. PROPOSED METHODOLOGY

3.1 Data Loading

Training data as well as testing data are separated from the input data. In order to begin ML research, raw data must be input. This raw data could be part of a database or a dataset composed of log files. First, it combined the eight files that comprised the dataset. Pandas also comes with a complete suite of tools for handling the imported data, which includes functions developed by sci-kit-learn, an open-source ML package for Python, as well as simulated data. The preprocessing data is given as the data loading output.

3.2 Preprocessing of Data

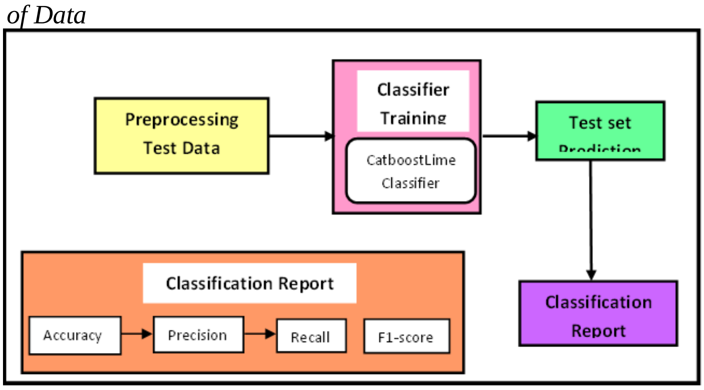

Fig. 1. Architecture for proposed work

Data loading uses the preprocessing data as input. In accordance with the "garbage in, garbage out" concept, the dataset was normalized using Standard Scaler. When dealing with Pandas, you may easily indicate missing data by using None or NaN. For this reason, cleaning a data frame of null values is essential. Rows and columns containing null values were removed using the drop.null() function since the dataset had a significant number of them. The dataset will be pre-processed to remove any extraneous information. The dataset should also have any unnecessary information removed. No longer are superfluous labels included in the dataset. After that, find and delete any null values from the rows and columns, and get rid of any empty columns. ML includes data loading, preprocessing, and the application of AI models. Figure 1 shows a classifier ensemble approach in addition to three traditional learning methods.

3.3 Machine Learning (ML)

1) Logistic Regression (LR)

For the purpose of making predictions about the value of a categorical dependent variable based on a collection of independent variables, LR is a subset of regression analysis in statistics. Always having a binary (two-category) dependent variable is standard in LR. Prediction and determining the probability of success are the major applications of LR. It is common practice to use maximum likelihood estimation to estimate the regression coefficients. One way to find out how much of impact independent variables have on dependent ones is to use the maximum likelihood ratio. Individual predictors' (independent variables') contributions are evaluated using the likelihood-ratio test. Then, for each scenario, we get its probability (p). The p-value is determined from this. The probability, or possibility, of developing coronary heart disease is thus provided [21].

2) LightGBM Classifier

Unlike previous gradient-boosting frameworks, LightGBM does not use the standard depth-wise or level-wise methods. By applying the gradient one-way sampling method, LightGBM effectively minimizes data volume, concentrating on important dataset parts rather than the complete data pool. Different from previous boosting methods, LightGBM has a number of benefits. Fast processing, decreased RAM utilization, improved prediction accuracy, and the ability to handle massive data quantities are all part of it. It is a flexible and economical choice since it enables parallel and GPU-based learning [19].

3) Catboost Classifier

Among the ML methods that are versatile, CatBoost can handle both numerical and categorical data. The ability to reduce overflight by addressing noise locations is a unique characteristic of CatBoost. To do this,assign previous values to densely populated areas with low-frequency features. Foundational to the development of the technique was the use of gradient-supported decision trees (GBDT). By removing the drif of prediction values and the gradient-best descent method bias, CatBoost is able to properly comprehend data and evaluate results. Without preprocessing, a previous value is inserted at places with low-frequency features as well as high density in models with overfitting concerns to decrease noise points. The model's generalizability is enhanced, and the features is minimized as a result. Category features may be managed with the CatBoost technique. The fact that CatBoost worked well with many different kinds of data and formats is an added bonus. Instead of using typical gradient techniques, which produce overfitting, this approach uses random permutations to assessment leaf values while determining the tree layout [19].

IV. Results And Discussions

4.1 Dataset

This research uses the following dataset for research. https://www.kaggle.com/cherngs/heart-disease-cleveland-uci. Our data comes from the UCI ML Repository's Heart Disease Dataset. There are more than 70 features in this dataset. Finding individuals with heart disease is its primary objective. The ratio of models produced during training is used in production settings. Understanding how the prediction results are obtained is the objective of including XAI techniques alongside the deployed model. An XAI module and a trained model get the data [18].

4.2 Analysis

In order to assess the NCD prediction model, True Negative (TN), False Positive (FP), True Positive (TP), as well as False Negative (FN)—are assigned to assessment metrics. In sum, (TP+TN) can decipher the model's accurate predictions, whereas (FN+FP) can decipher the model's inaccurate predictions. For the purpose of comparing and selecting models, the following assessment measures have been used: acc, specificity, rec, prec, and f-score [20]. The measures for assessment were established as

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

$$\text{Specificity} = \frac{TN}{FP+TN} \quad (2)$$

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

$$\text{Prec} = \frac{TP}{TP+FP} \quad (4)$$

$$\text{F} - \text{score} = 2*\frac{prec*rec}{prec+rec} \quad (5)$$

Table II: Proposed method Comparison

Methods	Prec	Rec	F1-score	Acc
LR	0.83	0.93	0.88	0.86
LightGBM Lime	0.98	1.00	0.99	0.99
Catboost Lime	1.00	1.00	1.00	1.00

Fig 2 shows the proposed strategy is compared to the accuracy of ML classifiers in training set. Calculate various performance measures, including the prec, rec,f1 score as well as acc of the system, based on the results, which are enlisted using the method with the proposed algorithm, which gives the best accuracy of 100% in training set.

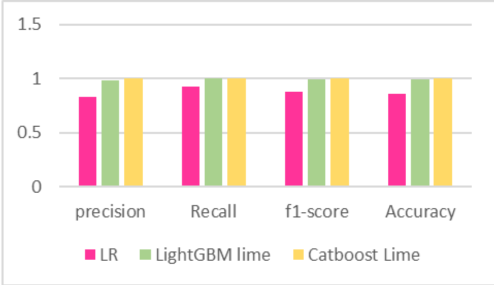

Fig. 2. Comparison graph for different models

Various approaches' performance parameters are compared in Table 2. Compared to other models like LR ,LightGBM lime and Catboost Lime, the proposed model seems to perform better across all parameters. On the heart dataset, the proposed model has an accuracy of about 100%. With a performance gap of 0.17%, this model beats LR and 0.02% LightGBM Lime. Additionally, Figures 3,4 and 5 show the graph for these models.

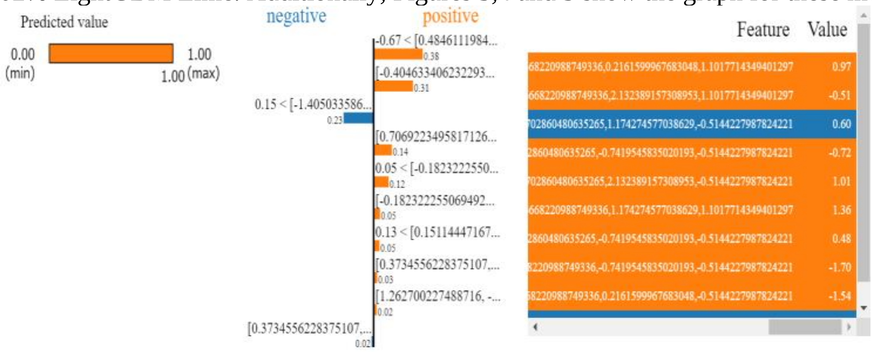

Fig. 3. LR

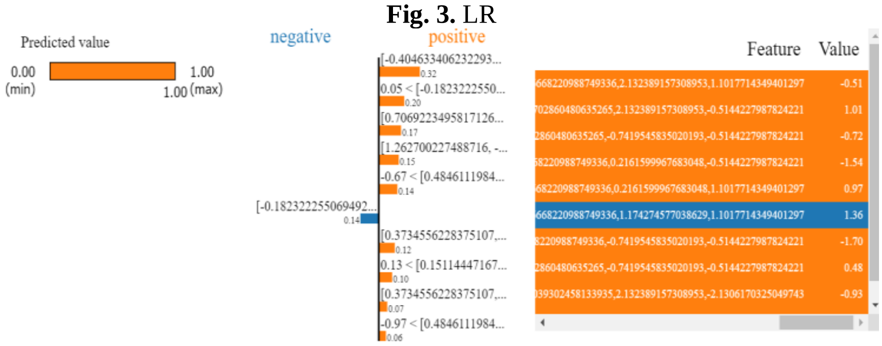

Fig. 4. LightGBM Lime

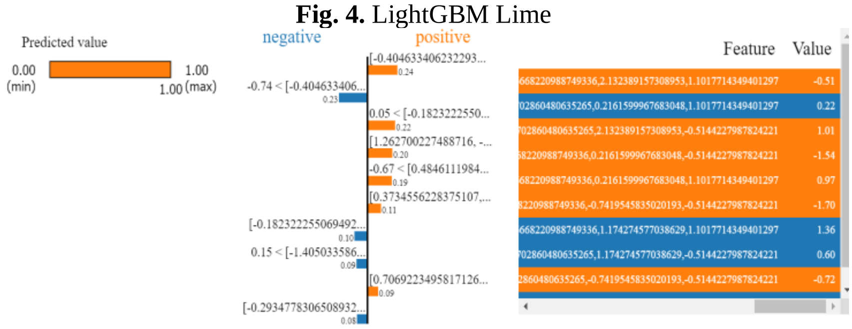

Fig. 5. Catboost Lime

V. CONCLUSION

For healthcare predictive modeling to be effective, explainability is key. Integrating predictive models into healthcare operations and earning the confidence of experts is challenging without openness. There has been a lot of buzz around XAI recently. Answering inquiries about the input, performance, output, as well as process (how) of the predictive models are information-based explanation questions that the XAI system should handle. User interfaces should include instance-based clarification questions to handle queries like "why," "what if," "how to be that," and "how to still be this" in response to users' examples that are meant to explain predictions. The ability to construct instances and comprehend the results obtained by the predictive model should be available to users. To assist their operations, healthcare institutions are actively creating ratio modeling systems. Integrating XAI may make healthcare predictive modeling more transparent. The transmission of information and adoption of models in healthcare operations rely on interactions between AI systems and health care practitioners. The healthcare industry is rapidly embracing ML. Different ML approaches such as LR, LightGBM and Catboost classifier XAI is done. Among this the Catboost classifier is concluded as providing a better result for the given dataset.

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