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Explainable AI: current status and future directions

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ABSTRACT Explainable Artificial Intelligence (XAI) is an emerging area of research in the field of Artificial Intelligence (AI). XAI can explain how AI obtained a particular solution (e.g., classification or object detection) and can also answer other "wh" questions. This explainability is not possible in traditional AI. Explainability is essential for critical applications, such as defence, health care, law and order, and autonomous driving vehicles, etc, where the *know how* is required for trust and transparency. A number of XAI techniques so far have been proposed for such applications. This paper provides an overview of these techniques from a multimedia (i.e., text, image, audio, and video) point of view. Advantages and shortcomings of these techniques have been discussed, and pointers to some future directions have also been provided.

INDEX TERMS Explainable Artificial Intelligence (XAI), Explainability, Interpretable Artificial Intelligence.

I. INTRODUCTION

In recent years, Artificial Intelligence (AI)-based applications have been used in various aspects of human life, such as science, business, finance and social networking, etc. AI-based algorithms have been successfully applied to all types of data (text, image, audio, video) in various applications, such as healthcare, defence, law and order, governance, autonomous industry, etc. An AI algorithm can now efficiently solve a classification, regression, clustering, transfer learning or optimizations problem [16]. This current day AI is mainly limited to a sub-branch known as machine learning (ML). Machine learning provides a computer with a set of examples (aka training data set), and let the computer learn from the example set. Once well trained, the computer can then answer questions related to what it was taught previously. Typically, this traditional AI is a *blackbox* that can answer "yes" and "no" type questions without elaborating how that answer is obtained.

In many applications, an explanation of how an answer was obtained is crucial for ensuring trust and transparency. An example of one such application is a medical application, where the doctors should be damn sure about a conclusion. They, for example, would like to know how AI decided whether someone is suffering from a disease by analyzing a CT scan image. AI-based systems are not 100% perfect. An

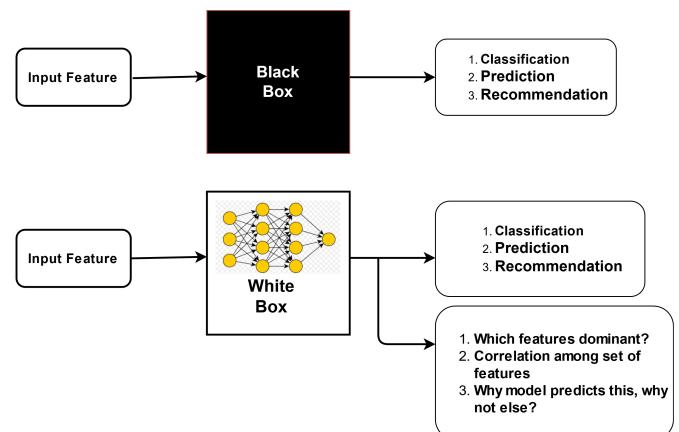


FIGURE 1: AI vs XAI

insight of how a result was obtained will therefore not only can induce trustworthiness but also can avoid life-threatening errors. In some other applications (e.g., law and order), answers to other "wh" questions (such as "why", "when", "where", etc.) could be required. The traditional AI is unable to answer these "wh" questions.

This explainability requirement lead a new area of AI research, known as Explainable AI (XAI). Figure 1 shows

how XAI can add new dimensions to AI by answering the "wh" questions that were missing in traditional AI. The XAI, therefore, has drawn a great interest from critical applications, such as health care, defence, law and order, etc., where explaining how an answer was obtained (i.e., answers to "wh" questions) is as important as obtaining the answer. In both academia and industry, XAI research, therefore, has become a priority. Although a number of work have been already proposed, more and more work is required to realize the full potential of XAI.

In this paper, we survey existing research on XAI from multimedia (text, image, audio, and video) point of view. Since each media is different than the other (i.e., image is different than video) in some sense, an XAI method applicable to one media may not be effective for another. We group the proposed XAI methods for each media, point out their advantages and disadvantages, and provide pointers to some future works. We believe that our classification of XAI methods will provide a guide and inspirations to future research in multi-modal applications (for example, XAI for defence where AI-based solutions are required for image, text, audio, etc.).

The rest of the paper is organized as follows. Section II discusses why classical blackbox AI. In Section III, we introduce XAI by discussing its scopes, objectives, and various tools proposed to realize explainability. This section also provides a classification tree outlining various XAI methods proposed for multimedia data. These methods are elaborated in the remaining sections. Section IV explains classification tree for XAI techniques, where transparent and post hoc techniques are explained. Section V discusses XAI methods applied to image data. Section VI discusses XAI methods applied to natural language processing (text data). Section VII and VIII gives understanding about how XAI works with video and audio type of data. Section IX explains about multi modal data like calibrated data from sensors in CSV format and also explains prevalence of XAI in defence and industrial applications for providing predictive maintenance to reduce cost of production and maintenance.

II. THE BLACKBOX AI

A. OVERVIEW

Blackbox models of machine learning are rapidly being used with a tag of AI-enabled technology for various critical domains of human life. The list of domains varies from socio-economic justice, cyber forensics, criminal justice, etc. But these AI-powered models are lagging to win the trust of naive people because these models are less transparent and less accountable [68]. For example, there are cases in criminal justice where the AI-enabled justice model release criminals on parole and grants bail. This leads to serious consequences among people and the government [69].

B. EXPLAINABILITY REQUIREMENT

"Explainability" is a need and expectation that makes "decision" of intrinsic AI model more transparent. This need will

develop rationale approach to implementing action driven by AI and also helpful for end users to understand [70].

In some basic level applications of AI, such as symptoms based health diagnosis, explainability is straightforward. But in the race of achieving more human level accuracy, researchers and scientists developed more complex algorithms. Neural network and deep learning based applications for decision making is quite elusive and less interpretable [10] [12].

1) Case Study 1: Oil Refinery Assets Reliability: Furnace Flooding Predictions

The Situation: Stable combustion is critical for uninterrupted operation of furnace. Due to unidentified factors, if stable combustion is interrupted, it leads to disastrous incident. For consideration of safety, it is highly required that such conditions need to be identified and acted upon. If such preventive measures are not taken, furnace may flood and eventually occurs in explosion. Such incident turns into shut down of plant which causes production delay and huge maintenance cost. Unplanned shutdown of industrial plant results in to huge financial loss.

The ML/AI Solution: A reliable prediction of furnace flooding is required to alert maintenance staff at least 30 minutes. To develop such kind of predictive maintenance model, it requires to collect calibration from all sensor data including weather and humidity etc. This model should predict flooding prediction at least 20 minutes prior.

Why Explainable AI: There could be n number of different factors which are responsible for flooding or shut down of combustion chamber or furnace. After shutting down the furnace maintenance staff needs to investigate cause of failure. This investigation helps to identify which sensor causes instability of continuous operation in furnace. Making prediction in such a way that helps to identify cause of failure with respect to different parts of combustion chamber. This explainability makes easier to address snag in industrial operation without wasting much time in investigation.

2) Case Study 2: Video Threat Detection

The Situation: In today's age, it is required to secure physical asset and human. A typical solution is to combine security personnel and digital camera for video analytics. Due to human eye limitation, it is not possible to watch every entry point and every video feed at all times. Absolute human supported surveillance may have certain error and threats of miss identification.

The ML/AI Solution: AI and deep learning based models evaluate video feeds to detect threats. These threats are later flagged for the security personnel. AI based object or face recognition models evaluate video feeds at air port to identify visitors who carry weapon or those are known criminals. These AI model should ignore normal employee or air port staff.

Why Explainable AI: Due to skewness or bias of model, it may possible that trained AI model detects innocent visitors

or employees due to certain weighted features in training samples. Such kind of incidents raises legality aspects for genuinity of such surveillance systems. Transparency in such systems are one of the crucial factor before framing one person as a criminal or suspect. Company of AI enabled surveillance system are required to provide justification in the court. An individual humiliated and searched publically by security forces leads to several legal consequences on government as well as airport authority.

C. USAGE

AI covers the entire ecosystem of computer-enabled interdisciplinary technologies. AI enables a group of technologies to behave more cognitively and context-oriented like human or animal rather than rule-oriented. AI is all about mimicking the complex cognitive behavior of all living entities on the earth [71].

There are many day-to-day usages of AI-enabled applications from object recognition, product recommendation in online shopping portals, chatbots for customer service and document processing, etc. AI is also one of the important tools for medical imaging and diagnosis. CT scan-based tumor diagnoses are effective and more accurate for certain conditions [71].

AI will have much more applications in the future. AI will be a reliable helping hand for doctors to do surgery and diagnoses. Autonomous vehicle driving is one of the upcoming areas where AI will be an important tool. AI can decide while on-road driving for elder people either by taking complete control or by assisting a human driver. For the criminal justice system, AI can make an important decision to declare a person guilty or non guilty [69]. AI-enabled decision-making systems provide better support for professionals. Because of the surge in applications of AI in corporate and industry, it becomes a hot topic for ethical concerns. AI usage policies will be decided by government agencies on aspects like privacy, optimization, etc. To make AI more reliable we need to make it more transparent and interpretable. This motivation makes upcoming AI development with aspects of explainability. This area of explainability oriented AI is known as XAI.

D. KEY ISSUES WITH EXPLAINABLE ML

The main reason behind the difficulty to understand and interpret the Black box ML model is either black-box function is quite complicated for a human to understand. Because deep learning-based models are recursive with non-differentiable recursive functions as active functions. Another reason is some functions are proprietary so it is not allowed to expose publicly. There is a belief in XAI researchers that interpretable ML models may reduce the accuracy of prediction and conclusion. Due to this belief, many researchers are now having good expertise in deep learning but not in XAI [11].

Many times explainable AI methods provide justifications that are not aligned with what the original method computes. If explainable methods are computing the same results and

predictions as original models then there is no need for an original model. Despite original and XAI models are computing the same predictions there are pretty good chances that both approaches are using a different set of features for making the same predictions. Hence, it is not faithful towards the computation of the black box. It also happens sometimes that the XAI model provides too much extra information which is not relevant to the original inferences of a black-box model.

For image processing domain saliency maps are considered the best tool for image classification. These maps are being useful to determine which part of an image is considered and which is omitted by the model for prediction. But saliency maps are not explaining how different parts of images are contributing to the given prediction. As shown in Fig. 2 Saliency maps are not able to demonstrate except where neural network model is focusing.



FIGURE 2: Saliency does not explain anything except where the network is looking. We have no idea why this image is labelled as either a dog or a musical instrument when considering only saliency. The explanations look essentially the same for both classes. Credit: Chaofen Chen, Duke University [11]

Consider, for instance, a case where the explanations for multiple (or all) of the classes are identical. This situation would happen often when saliency maps are the explanations, because they tend to highlight edges, and thus provide similar explanations for each class. These explanations could be identical even if the model is always wrong. Then, showing only the explanations for the image's correct class misleads the user into thinking that the explanation is useful and that the black box is useful, even if neither one of them is.

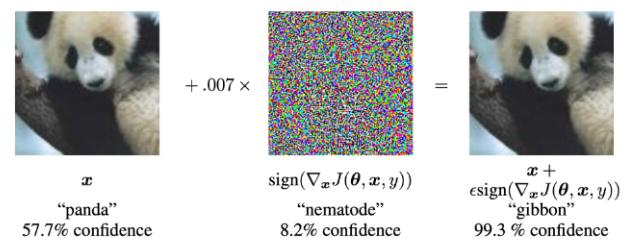


FIGURE 3: Panda image was tampered by adding some adversarial noise [72]

Fig. 3 illustrates such an example where an image of a Panda is predicted as a Gibbon with high confidence after

the original Panda image was tampered by adding some adversarial noise.

III. XAI AS A TOOL TO OPEN BLACK BOX

In section III-A objectives like transparency, trust, bias and fairness of XAI are discussed. Section III-B provides overview about different scopes of XAI.

A. OBJECTIVES

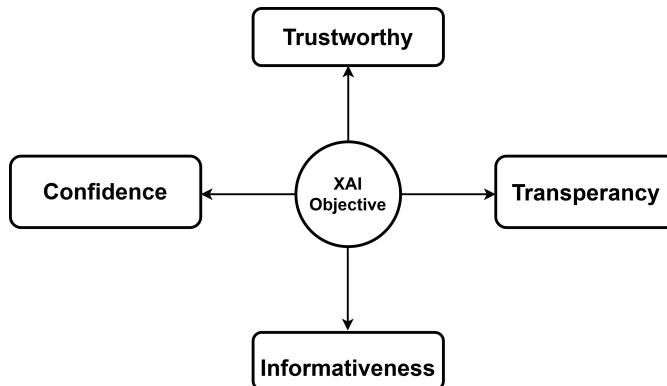


FIGURE 4: Objectives of XAI

The main objective of XAI is to answer the "wh" questions related to an obtained answer. For example, XAI should be able to answer "why a particular answer was obtained?", "how a particular answer was obtained", "when a particular AI-based system can fail?" [13] [14] [15]. By doing this, XAI can provide trustworthiness, transparency, confidence, and informativeness (Figure 4).

1) Transparency and Informativeness

XAI can enhance transparency as well as fairness by providing a justification that can be understood by a layman. The minimum criteria for a transparent AI model are it should be expressive enough to be human-understandable.

Transparency is important to assess the performance of the XAI model and its justification. Transparency can assure any false training to model that causes vulnerabilities in the prediction that makes a huge loss in person to the end consumer. False training is possible to tweak the generalization of any AI/ML model that leads to providing unethical benefits to any party unless it is not made transparent.

2) Trust and confidence

Trust is one of the important factors that makes humans rely on any specific technology. A logical and scientific justification for any prediction and conclusion makes humans favor the prediction or conclusion made by AI/ML algorithms.

3) Bias Understanding and Fairness

Bias and variance trade-off in AI/ML model makes XAI promote fairness and helps to mitigate bias (bias-variance trade off) of prediction at the time of justification or interpretation [59].

B. SCOPE

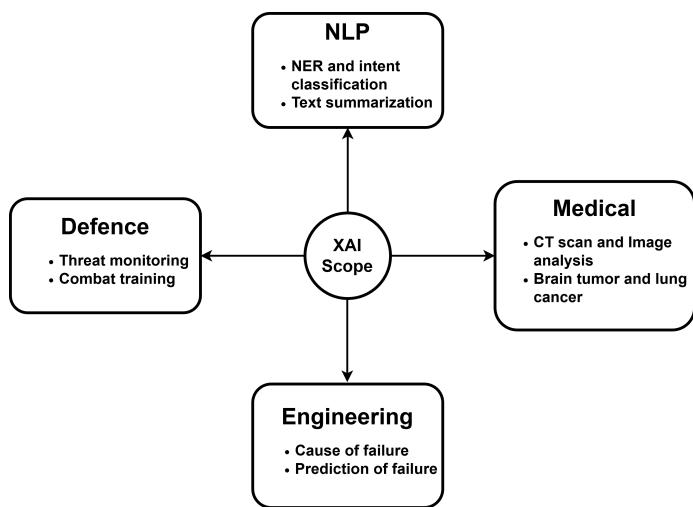


FIGURE 5: Scopes of XAI

Ideally, scope of XAI can be as broad as scope of AI. Major scopes are NLP (natural language processing), health care, engineering, and defense. NLP and engineering comprise banking, finance, digitization, and automation. These scopes of XAI are depicted in Figure 5.

1. Data Protection: European Union and its regulatory body have a 'right to explanation' clause. That makes to enables explanation from XAI algorithms.

2. Medical: XAI can diagnose a patient by observing his/her past medical records. Using AI/ML algorithms in the medical image processing domain it is easier for medical experts to diagnose patients with malignant cancer tumors and other lung diseases.

3. Defense: XAI in defense practices becomes crucial because of automated weapon and surveillance systems. XAI also provides good second-hand support during combat mode training and real-time combat tactics.

4. Banking: The banking system is one of the biggest financial sectors which affects human life the most. In day-to-day life, there are many fraud transactions and cones by cheaters. Well-trained XAI models can help to investigate fraudulent transactions and help to reduce false positives cases.

IV. CLASSIFICATION TREE

XAI techniques are classified in two categories of transparent and post-hoc methods. Transparent methods are such methods where the inner working and decision-making process of the model is simple to interpret and represent. Bayesian model, decision trees, linear regression, and fuzzy inference systems are examples of transparent models. Transparent methods are useful where internal feature correlations are not that much complex or linear in nature. Figure 6 depicts detailed classification of various XAI techniques and approaches with respect to various types of data [28].

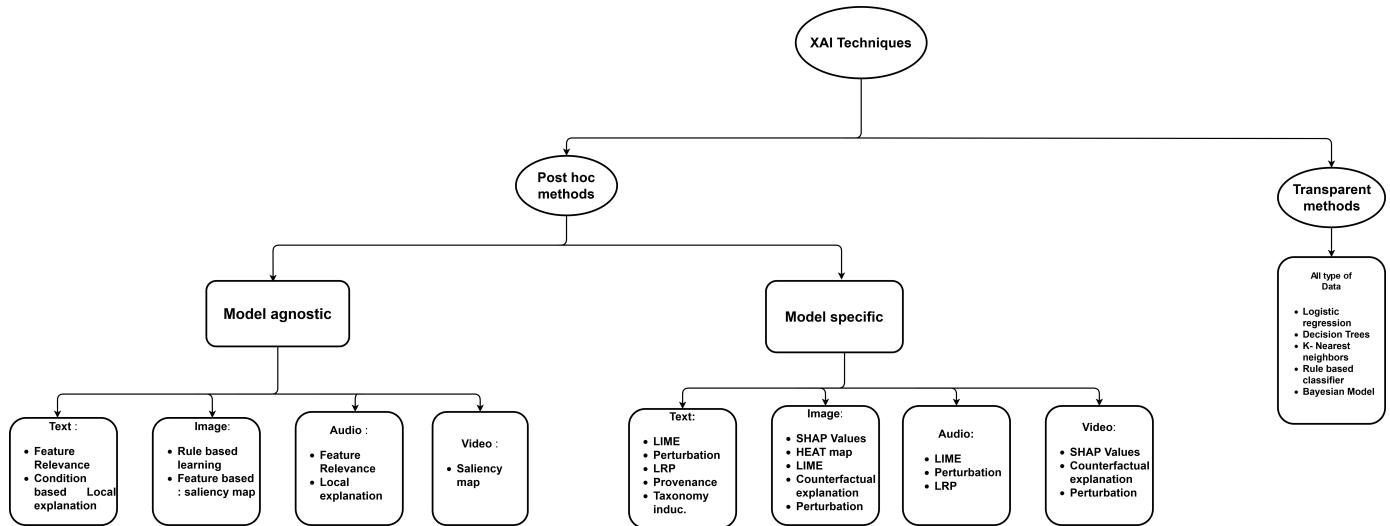


FIGURE 6: XAI classification with respect to type of data

A. POSTHOC METHODS

When there is a nonlinear relationship or higher data complexity exists, posthoc methods are useful to interpret model complexity. In this case, the posthoc approach is a useful tool to explain what the model has learned when it is not following a simple relationship among data and features.

Result-oriented interpretability methods are based on feature summary's statistical and visualization-based presentation. statistical presentation denotes statistics for each feature where the feature's importance is quantified based on its weight in prediction.

A post-hoc XAI method receives a trained and/or tested AI model as input, then generates useful approximations of the model's inner working and decision logic by producing understandable representations in the form of feature importance scores, rule sets, heat maps, or natural language. Many posthoc methods try to disclose relationships between feature values and outputs of a prediction model, regardless of its internals. This helps users identify the most important features in an ML task, quantify the importance of features, reproduce decisions made by the black-box model, and identify biases in the model or data.

Some post-hoc methods, such as Local Interpretable Model-agnostic Explanations, extract feature importance scores by perturbing real samples, observing the change in the ML model's output given the perturbed instances, and building a local simple model that approximates the original model's behavior in the neighborhood of the original samples. Posthoc methods are further classified in model agnostic and model specific. **Model-specific techniques** supports explainability constraints with respect to learning algorithm and internal structure of given deep learning model. **model-agnostic** techniques applies pair wise analysis of model inputs and predictions to understand learning mechanism and to generate explanations.

It is observed that global methods are capable to explain

for all data sets while local methods are limited to specific kind of data sets. In contrast, **model-agnostic** tools can be used for any AI/ML model. Here pairwise analysis of input and results plays a key role behind interpretability. In next sections, we have discussed model specific techniques like feature relevance, condition based explanations, rule based learning and saliency map.

B. TRANSPARENT METHODS

Transparent method like logistic regression, support vector machine, Bayesian classifier, K nearest neighbour provides justification with local weights of features. Models falls under this category satisfies three properties named as algorithmic transparency, decomposability and simulability.

Simulability stands for simulation of model must be executed by a human. For human enabled simulation complexity of model plays an important role. For an example sparse matrix model is easy to interpret compared dense matrix because sparse matrix model ia easy to justify and visualize by humans.

Decomposability stands for explainability of each aspect of model from input of data to hyper parameters as well as inherent calculations. This characteristics defines behavior of a model and its performance constraints. Complex input features are not readily interpretable. Due to this constraints such models are not belongs to category of transparent model.

Algorithmic transparency defines algorithm level interpretability from input of given data to final decision or classification. Decision making process should be understood by users with transparency. For an example linear model is deemed transparent because error plot is easy to visualize and interpret. With help of visualization user can understand how model is reacting in different situation.

The transparent model is realized with the following XAI techniques.

1) Linear/Logistic Regression

Logistic Regression (LR) is a transparent model to predict dependent variable which follows property of binary variable. This method assumes there is a flexible fit between predictors and predicted variables.

For understanding of logistic regression, model it requires audience to have knowledge of regression techniques and its working methodology. Due to this constraints, depending upon type of audience logistic regression falls either in transparent or posthoc methods. Even though logistic regression is the simplest form of supervised classification techniques, its mathematical and statistical concepts are need to be taken care off.

2) Decision Trees

Decision trees is a transparent tool which satisfies transparency in a large context. It is a hierarchical decision making tool. Smaller scale decision trees are easily simulatable. Increment in number of levels in trees make it more algorithmically transparent but less simulatable. Due to its poor generalization property, ensembling of trained decision trees are useful to overcome poor generalization property. This modification makes decision tree tool less transparent.

3) K-Nearest Neighbors

KNN (K-Nearest Neighbors) is a voting based tool that predicts class of test sample with help of voting the classes of its k nearest neighbors. Voting in KNN depends on distance and similarity between examples. Simple KNN supports transparency, algorithmic transparency and human centric simulation. KNN's transparency depends on the features, parameter N and distance function used to measure similarity. Higher value of K impacts simulation of model by human user. Complex distance function restricts decomposability of the model and transparency of algorithmic operation.

4) Rule based learning

Rule based model defines rule to train model. Rule can be defined in the simple conditional if-else form or first order predictive logic. Format of rules depends on type of knowledge base. Rules provides two advantages to this type of model. First, since format of rules are in linguistic terms it is transparent for user to understand. Second, it can handle uncertainty better than classical rule based model [25]. The number of rules in model improves the performance of model with compromising interpretability and transparency of model. Model with less number of rules can be easily simulated by human.

5) Bayesian Model

Bayesian model are probabilistic model with notion of conditional dependencies between set of dependent and independent variables. Bayesian model is transparent enough for end users who are having knowledge of conditional probability. Bayesian model are enough suitable for all three properties

decomposable, algorithmic transparency and human simulation. Complex variable dependency may affect transparency and human simulation for bayesian model.

C. MODEL SPECIFIC

Model specific XAI models are realized using following techniques.

1) Feature Relevance

It is always important to figure out the most impactful features which are crucial for decision makings. For this feature, importance is introduced. Feature importance shows the impact factor of each feature in derived decisions [26]. Along with feature importance, correlation among features is also useful for explainability. In AI-based medical diagnosis model, feature correlation in training data is one of the driving forces for diagnosis.

2) Condition based Explanation

Condition based explanation is required on the basis of "why", "why despite" and "why given". Some specific observed inputs plays key role to justify prediction. By asking "Why?" oriented questions, model will provide all possible explanations with set of conditions. This condition set is generated with completeness phenomena. "what if" provides hypothetical reasoning for counterfactual justification. A simple logical model converts user inputs in to the form of constraints based inputs and provide justification that whether constraints are being satisfied in the form of conditions.

3) Rule based learning

Explainability is required because ML model output is numerical and neural network is too much complex that normal user can not understand the complexity of hyperparameters and its effect on final prediction.

After getting some insightful understanding of trained model and interpretability of results, suitable approach is to explain derived results to customers and naive users is translation of those insights into rules such that it can provide full transparency for XAI [25]. Once rules are framed for all possible predictions, It makes even the most complex neural network model transparent.

4) Feature based saliency map

Saliency maps are generally used with image processing areas of applications to show what parts of video frames or images are the most significant for derived decision of CNN.

XAI saliency map is a tool which is useful showcase inner working of DNNs. Gradien computation using back propagation algorithm are used as quantified measures to project intensity of colours on plane.

D. MODEL AGNOSTIC

Model agnostic techniques are also applied for text, image, audio and video. various techniques like LIME, perturbation,

LRP, SHAP, provenance and taxonomy inductions, counter factual explanations are applicable on different type of data like text, image, audio and video.

1) LIME- Local Interpretable Model-agnostic Explanations

Model agnosticism specifies the property that LIME is able to provide justification for any type of supervised learning model's prediction. This technique is applicable for any sort of data like image, text and video. This means that LIME is able to handle any supervised learning model and provide justification.

LIME provides local optimum explanations which computes important features around the vicinity of given particular instance to be explained. By default it generates 5000 samples of the feature vector which are following normal distributions. After producing normally distributed samples it finds the target variables for samples whose decisions are explained by LIME.

After obtaining local generated dataset and their predictions it assigns weights to each of the rows how close they are from original samples. Then it uses a feature selection technique like lasso or PCA (Principle Component Analysis) to get significant features. Detailed discussion about LIME is referred in section V-A.

LIME has found much success and support in the field of XAI and is implemented for text, image, and tabular data. One noticeable observation about LIME is that it is applicable and extendable to all significant machine learning domains. In the domain of text processing, embeddings and vectorization of given word or sentence can be considered as a basic unit for sampling. For Image, segmented parts of Image are considered as samples for input.

2) Perturbation

Perturbation helps to generate desired explanation drivers and analyze impact of perturbed features on the given target. It provides summary of all features for given perturbed results.

In perturbation mechanism local changes are observed on target results and perturbation scores are assigned to all features using LIME or SHAP methods.

Perturbation method is easy to implement and it is not applicable to specific architecture of model. This method can be applied to type of AI/ML model. Disadvantage of perturbation method is, it is computationally expensive if number of features are relatively greater than normal average. As there are more number of features it takes more time to evaluate combination of all features.

This scenario occurs specifically when dimensions of input are more because number of combinations of all features grows rapidly. Moreover, this mechanism can underestimate the selected feature's contribution because respective feature reaches saturation level in perturbation such that perturbing them do not have any impact on derived results.

3) LRP: Layer-wise Relevance Propagation

LRP is useful to unbox complex neural networks. It propagates predictions backward in the neural network. For backward propagations specific rules are designed.

4) Provenance and taxonomy induction

Provenance and taxonomy induction are logical inference based techniques to justify result based on partially derived results. In section VI-A it is discussed with detail [80]. Comprehensive analysis of important XAI techniques is presented in Table 1.

V. XAI AND IMAGE

Explanations in XAI are often categorized into two main aspects. The first category is whether the given explanation is limited to the given conclusion of a model or it describes the entire prediction process which includes training aspects also. The second category differentiates between whether explanation comes directly from the prediction process or it requires posthoc analysis [1] [23].

Popular instance-level explanation methods for image classification such as LIME [2], SHAP [3] and LRP [4], typically create feature importance rankings. Although insightful, these methods have clear drawbacks: they do not determine the optimal explanation size, they do not account for feature dependence, and they are related to only one prediction class.

A. LIME

Local interpretable model-agnostic explanations (LIME), as the name suggests it interprets the model locally and explains the classification of the model in a faithful manner. In LIME, the prediction of the model is used as labels for supervised training to train the XAI model.

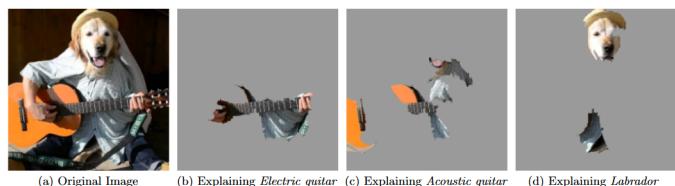


FIGURE 7: Explaining an image classification prediction made by Google's Inception neural network. The top3 classes predicted are "Electric Guitar" ($p= 0.32$), "Acoustic guitar" ($p= 0.24$) and "Labrador" ($p= 0.21$) [73]

Sparse linear models are a useful tool to explain LIME-based justification [5]. Using a sparse linear model it is possible to highlight important pixels with their weights for a particular respective class as shown in Fig. 7. This set of important pixel areas give intuition as to why the model would think that class may be present. As described in figure 5 important pixel-based explanation is given. It interprets the original image as electric guitar, acoustic guitar, and Labrador with respect to the confidence score of 0.32, 0.24, and 0.21.

Approach	Advantages	Drawbacks	Future Directions
LIME [1][4]	Plug and play based	The resulting explanations are found to be unstable. The ranking does not account for feature dependence.	To reduce local fidelity of justification , Non redundant instance based justification can be tried.
SHAP [5][8]	Optimized for speed up	Small perturbations with no change in prediction leads to different explanation.	SHAP can be used to define context of each feature.
LRP [0]	Suitable for neural network	Low abstract level explanation with relevance map	With layer wise attribution of new class discriminativity can be increased
Heatmap	Feature importance based presentation	Individual pixels are typically not meaningful for humans less interpretable	It is a self explainable approach for classification but future work requires text-based presentation
SEDC and SEDC-T [6][7]	More human centric explanation	More than one irreducible explanation	counter factual analysis for text based explanation
Feature Importance [77][31][32]	Feature weight based explanation	Explanation is limited with respect to only local features. May drive attention of user towards from important global dependency.	Reduction of local fidelity on prediction
Induction [77]	More convenient for programming	Such techniques assume that end users can understand specific representations, such as first-order logic rules and reasoning trees.	Generalization is required for diverse data
Provenance [77][33]	Natural language based explanation	It is more accessible for lay users but not much compatible for validation because it is based on natural language.	validation of justification is required for more reliability.

TABLE 1: Analysis of various XAI approaches

B. SHAP (SHAPLEY ADDITIVE EXPLANATIONS)

The main objective of SHAP is to understand the prediction of an input A by computing the decision-making contribution of each feature for the classification. SHAP computes Shapley values using coalitional game theory. It is a technique described by Shapley (1953) [9] as an approach for assigning a reward to game players according to their contribution to the game. SHAP assigns each feature an importance value for a particular prediction [6].

The key difference between LIME and SHAP is the process to assign weights to the regression linear model. LIME uses cosine measure between the original and the perturbed image. SHAP, the weights are determined using the Shapley formula. LIME and SHAP methods have their drawbacks: they do not determine the optimal explanation size, they do not account for feature dependence, and they are related to only one prediction class.

C. COUNTERFACTUAL VISUAL EXPLANATIONS

For human psychology, it is convenient to explain by giving contrastive explanations rather than giving direct explanations to the conclusion or prediction of the machine learning model. We can explain by providing reasons, why only a certain class is selected and why others are rejected.

For explainability, we generally try to provide the explanation on the basis of the selection and rejection of the specific alternatives or outcomes. For given scenario, why only outcome A selected not B. A useful tool to provide such a discriminative explanation is using counterfactuals. We can use counterfactuals to provide reasonably valid arguments at the end of the conclusion by machine learning model which is supported by either deep learning or classical statistical modeling. With the nature of counterfactuals, a certain set of features are defined that can change the decision of the model. If those features are not available then the final conclusion of the model will be changed. It is argued that they are more likely to comply with recent regulatory developments such as GDPR. The counterfactual approach helps to understand and satisfy three important needs of interpretability: how an interpretation of a model was made, it provides the scope to tweak with adverse decisions, and gives clues to receive intended results in prediction.

There is a scenario of classification in classes A, B, and C. let's say there is a feature set (a1, a2,....., a10) which are relatively required to get prediction A. For Given input result of prediction is class B because feature set (a11,a12,....a20) is present and feature set (a1, a2,.....,a10) is absent. The approach with the feature set based interpretation leads to

smooth convincing in human-critical domains like Crime, Forensic. [7].

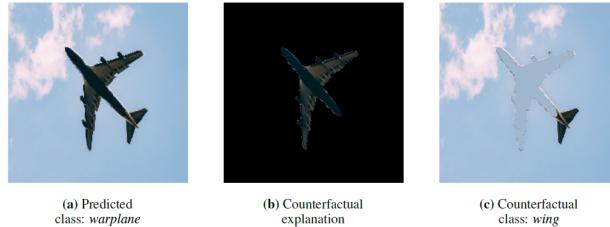


FIGURE 8: Figure a depicts an image which predicted as warplane by model. Figure b and c shows that by removing body and main wings from plane model predicts tail portion as wing rather than Plane. So figure b is an critically minimum portion in an image to get classified as Warplane. [8]

This evidence-based approach of counterfactual is known as Search for EviDence Counterfactual for Image Classification(SEDC). Fig. 8 explains how body of plane i s minimally critically portion to classify as an Image.

As per the research of dhurandhar et al. [7] there is a notion of pertinent positive(PP) and pertinent negative(PN). A pertinent positive (PP) is a factor that is minimally required for the justification of the final decision of the model. the pertinent negative is a factor whose absence is minimally required for justifying the conclusion. Figure 6 denotes that the plane body is critical minimum evidence for getting classified as Warplane.

The advanced approach is also under research which is known as SEDC-T. Where T stands for predefined target class, not just another class. In SEDC segments images are removed until the predicted class is not changed but in SEDC-T segments are removed from Image until pre-defined class is reached.SEDC-T gives a more detailed explanation of why the image is not predicted as a correct class rather than just explaining the reason behind the prediction of the incorrect class.

D. XAI AND HEALTHCARE

XAI and healthcare is an effective combo of digital technology. In the trend of AI-based diagnosis systems, trust over AI-based conclusions is a matter of serious concern. Trust is an important factor for the perseverance of AI in the medical and healthcare segment of the digital industry [42]. If-else diagnosis models are inherently explainable because it consists of feature value sets and will assign a score based on a feature value of an instance case of health diagnosis. If-else-based explainable medical diagnosis systems are well suited for external symptomatic disease diagnosis [43]. Whether a given deceased person is having asthma or not can be detected by checking whether the symptoms list of the person having what amount of matching criteria with If-else based feature values. For example, if the patient is already having a past history of respiratory illness and cough then there are higher chances of having asthma.

This step-by-step analysis provides a very effective explanation for external symptoms. To cover a broad spectrum of XAI it is required to make the justification that is independent of the AI model. Such methods are known as model agnostic XAI methods. LIME (Local Interpretable Model-Agnostic Explanation) [2] is an example of a model agnostic method. LIME is a framework to quantify weights of all factors which are there to make conclusion or prediction. There are other model agnostic XAI techniques also like SHAPLEY [6]. Deep learning is a very important tool for accurate medical diagnosis but its black-box approach for prediction and conclusion makes it restricted for the certain critical area of human medical science.

1) Explainability methods for XAI-Healthcare

There are two types of methods for an explanation of medical imaging. One method is based on attribution based and another method is based on perturbation.

Attribution LIME is an attribution-based approach for medical image diagnosis. In the attribution-based methods, one needs to determine the contribution and weight of each feature. The success of attribution-based explanation is based on the generality of assigned weights for a given prediction or conclusion at the end of the model. Heat maps are an example of attribution maps. Fig. 9 explains how various feature set with respect to different kernels in VGG 16 demonstrates heat map feature weights.

DeepTaylor [41] has provided an approach to generating specific positive evidence for a given prediction. The deepTaylor approach of XAI is useful for justifying CNN-based classification. It explains without changing underlying architecture, this property makes it an effective XAI tool. DeepExplain provides a unified framework using gradient and perturbation-based attribution methods [44] [52].

DeepLIFT (Deep Learning Important FeaTures) is a technique based on decomposing the prediction of a neural network for specific input. The entire backpropagation process is observed along with observation of weight and bias on each neuron on every layer of the entire architecture. Based on a variety of weights on neurons specific scores are assigned to each feature of input [45].

Perturbation In this approach, input features are getting changed to observe the impact on final prediction at the end of the last layer in the neural network. Perturbation can be achieved by masking or editing certain input features and observations are recorded as model start training using forward pass and backward pass. This is similar to the sensitivity analysis performed in parametric control system models [50] [51].

The sensitivity of each feature based on input variation is recorded. This continuous observation makes the XAI practitioner justify different predictions at the end of the neural network. Rank assignment to various features is similar to deep explain. one drawback of deeplift approach is computationally expensive. After each forward and backward pass of a number of iterations, observation of sensitivity with respect

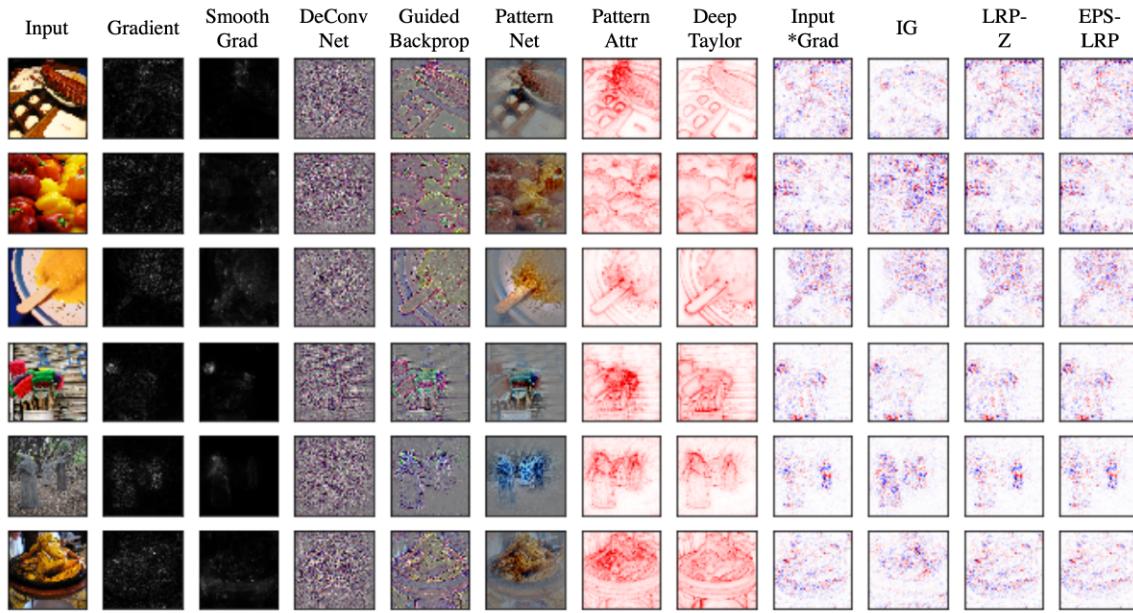


FIGURE 9: Attributions of VGG-16 with images from Imagenet using the methods implemented in [42]

to features is recorded. Occlusion is an important technique for extracting important features from given Image [46] [47]. It is a straightforward model to perform a model agnostic approach that explores the latent feature ranking of a model. All pixels occlusion is computationally expensive, hence 3×3 and 10×10 tiles are generally useful for occlusion [48] [49]. Trade-off is there with respect to the size of tiles and accuracy.

2) XAI for Health care applications

Brain Imaging CNN is a tool for accurate Image classification. Features-based classification of Alzheimer's using CNN gives robust [64] classification and accuracy.

Using post hoc analysis we can understand there is a certain amount of overfitting is available due to certain features. In post model analysis it is possible to tweak certain hyperparameters so that more accurate results are possible to extract. Methods like Guided backpropagation (GBP), LRP, and DeepShap are useful for brain imaging and classification [65].

During surge of COVID 19 pandemic AI along with explainability plays an important role in covid 19 diagnosis. Major steps are depicted in Fig. 11.

- Extraction of lung information from chest CT scan.
- Classification of CT scans in the category of covid positive and negative using convolution.
- Localization of lung symptoms like ground glass and crazy paving in CT scans.
- Provide well-documented justification [66].

Fig. 10 explains neural network architecture of covid 19 detection model to test presence of covid 19 by analysing CT scan of lung. The sequence of 3 consecutive slices (224×224)

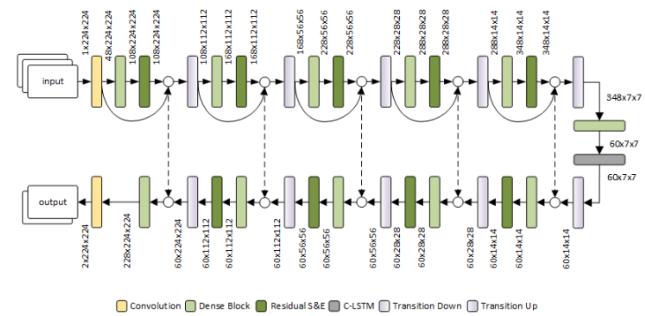


FIGURE 10: The proposed segmentation architecture, consisting of a down sampling path (top) and an up sampling path (bottom), interconnected by skip connections and by the bottleneck layer. [66]

lungs CT scan, which are fed in pipeline individually and combined through a convolutional LSTM layer. The architecture of convolutional LSTM is described in figure 9. The resulting feature maps are then processed with downsampling. Downsampling generates five sequences of dense blocks and then squeezing-excitation is performed. At last, max-pooling operation is performed. At the end, six channel segmentation is generated for lobs and nonlungs area of CT scan as shown in Fig. 11.

VI. XAI AND TEXT

In general, Natural language processing (NLP) systems are having inherent explainability. NLP major applications using machine learning are sentiment analysis, hate speech detec-

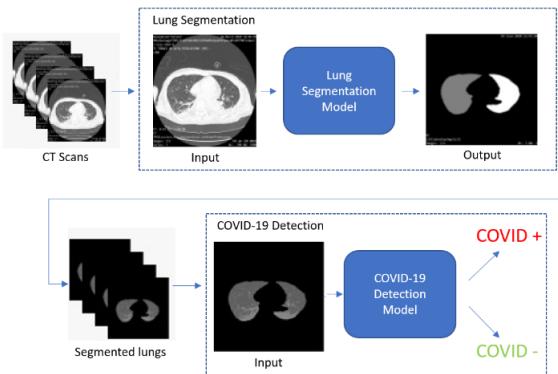


FIGURE 11: Overview of the COVID-19 detection approach for CT scan classification as either COVID-19 positive or negative. [66]

tion, text summary generation [17] [18]. For all these applications machine learning models are used like decision trees, sequential modeling, logistic regression, a bag of words, skip grams [19] [61] [62]. Due to the recent advancement in word embeddings, It gives more efficiency to black-box-based inferences and conclusions [20]. One drawback of this increased efficiency is these models are less interpretative and less explainable. Digital ethics are a big concern as far as reliability is concerned over black-box systems. Hence Explainable AI makes more sense for NLP-based applications of AI and Deep Learning [21] [22]. Figure 7 consists of various explanation techniques for NLP like a saliency heat map, saliency highlights, declarative explanation, and natural language inference.

A. EXPLAINABILITY TECHNIQUES FOR NLP

There are five different techniques that are useful for providing mathematical justification for the conclusion and classification of AI-based NLP system [27] [55].

Feature importance: This technique is based on the weight of various features based on feature engineering concepts. Specific scores are going to be assigned to individual features based on their contribution to the final prediction. This technique is based on various features of NLP. Some features are handcrafted or annotated, which are extracted manually by feature engineering [31], lexical features based on tokens and n-gram [33], or latent features using LDA [34] and Attention mechanism [32]. Text-based features are more convenient for the human to understand just because they in form of a readable text. There are certain disadvantages also with hand-crafted features due to their local optimum derivations.

Example driven: In an example-driven approach, examples of text being provided are in favor of the final conclusion and some are against the final conclusion. This approach leads to an instance and label base justification for given prediction and conclusion. They are similar in the essence

of the neighborhood or clustering-based approach.

Provenance: This approach is based on the reasoning steps. It is thoroughly validated approach for reasoning based derived justification. In this approach, final result is derivation from series of reasoning steps. This is best technique for automatic question answer explanation [35].

B. VISUALIZATION TECHNIQUES FOR NLP

Presentation is a crucial segment of XAI as far as justification is concerned for a naive person. There are many ways for a visualization based on chosen XAI approach or technique. For an effective attention-based mechanism that gives weightage to different features, the saliency map-based technique is an important tool that demonstrates scores of individual features [36] [29]. Here, we have provided a detailed description of different visualization techniques in fig.6.

Saliency: There is a strong correlation between feature score-based justification and saliency-based visual presentation. There is many research-based demonstrations where saliency-based visualization technique is chosen. Saliency-based visualizations are popular because they present visually perceptive explanations and can be easily understood by different types of end-users [24].

Raw declarative representations: This technique is based on the presentation of logic rules, trees, and programs. It contains sequential derivation based on logic rules [40].

Natural language explanation: In this explainable technique, the explanation is provided in more comprehensive natural language [38]. It is an application of the generative neural network model where natural language sentences are generated by the NN (Neural network) model [30]. For this purpose, sophisticated and dedicated models of particular domains eg. pharma, medical, crime, etc [39]. are trained and deployed in production. This model is usually known as the generative model. Fig. 12 and Fig. 13 are describing saliency based highlighting and POS based tags for visualization.

C. XAI AND HATE SPEECH DETECTION

In this section, we are explaining hate speech detection using XAI. This section demonstrates explainability techniques for hate speech detection using XAI [60] [63]. There are text classification based techniques which are useful for providing more insights about trained model for hate speech detection and used data set for training [54] [57] [58]. This projected insights are useful to make trained model more accurate for hate speech detection. Fig. 14 shows saliency map for classification of hate vs offensive speech. Fig. 14 shows how certain key words draws classification towards specific class of hate speech with higher weight.

Shapley values are useful for feature importance based analysis of hate speech. Feature importance map like saliency maps are useful for visualization. Gradient explainer based approach is also useful but generate feature independence based justification.

- if I can give this restaurant a 0 I will we be just ask our waitress leave because someone with a reservation be wait for our table my father and father-in-law be still finish up their coffee and we have not yet finish our dessert I have never be so humiliated do not go to this restaurant their food be mediocre at best if you want excellent Italian in a small intimate restaurant go to dish on the South Side I will not be go back
- this place suck the food be gross and taste like grease I will never go here again ever sure the entrance look cool and the waiter can be very nice but the food simply be gross taste like cheap 99cent food do not go here the food shot out of me quick then it go in
- everything be pre cook and dry its crazy most Filipino people be used to very cheap ingredient and they do not know quality the food be disgusting I have eat at least 20 different Filipino family home this not even mediocre

FIGURE 12: Saliency highlighting [37]

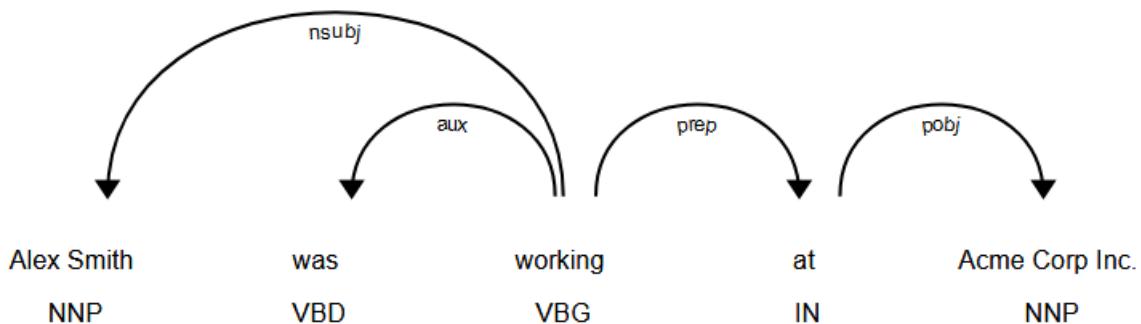


FIGURE 13: Visualizaton of POS tags [81]



FIGURE 14: Directed hate misclassified as offensive language with very high confidence(94%). The two words “bitch” and “faggot” are the two main positive contributors to the score. Although the two words are indeed offensive, they misdirect the classifier which misses the clear hate emerging from the tweet [53].

VII. XAI AND VIDEO

Local optimum justifications are an effective technique for the image domain. A model agnostic technique like LIME shows a good success rate using local explanations. . For video analysis and explainability, frame-wise decomposition of video is applied.

LRP is another popular technique. LRP assumes that it can access the internal architecture of a given complex neural network. LRP access model’s internal weight, bias, and

activation function for backward propagation. LRP is structured as a tool for pixel-wise decomposition for relevance to a decision. LRP satisfies certain conditions for developing justifications as below.

- The relevance difference of each layer must converge must sum at the final layer of the model.
- The relevance difference at any neuron of a given layer apart from the final layer is the sum of incoming relevance differences to that layer.

Other techniques like LIME are useful to provide justifications to develop explanations for models without accessing internal structure and weights. LIME approximates decisions by many sampled inputs. LIME is effectively applicable to data like text, image, and tabular data.

The most popular of these techniques, known as Local Interpretable Model Explanations or LIME, seeks to approximate the decision function by many closely sampled input points, which all center around the input point to be explained. It can then attribute positive or negative influence on the decision function to the differences in the sampled inputs, and overlay this on the original input.

VIII. XAI AND AUDIO

In this area, much research is yet to be done. For linguistic applications, audio waves are converted into text form. After converting into text, NLP-based XAI techniques are applica-

ble. Such techniques comprise lime, perturbation, SHAP and taxonomy-based inductions [79] [56].

Now a days, auto speech recognition powered voice assistant like alexa and siri are being used more frequently by users [78]. Audio waveform based key word classification for virtual agents is more convincing along with visual presence of agent rather than only voice or text based output [74].

It is observed that the visual presence of virtual agents in graphical 2d or 3d forms develops trust in the XAI systems. To evaluate this observation, a user study is conducted in which a virtual agent demonstrates XAI visualization of a neural network-based speech recognition model. This model classifies audio keywords with respect to their spectrograms. In this study, users are classified into three groups. First, interact with the text. Second, interact with voice, and Third, interact with virtual agents [74]. The results show that the visual appearance of an agent gains more trust rather than only text or voice-based interactions.

LIME framework is applied to generate XAI visualization to understand voice classification. Model agnostic characteristics of LIME make it applicable to any sort of input data. Fig 15 shows XAI visualization of the keyword "House".

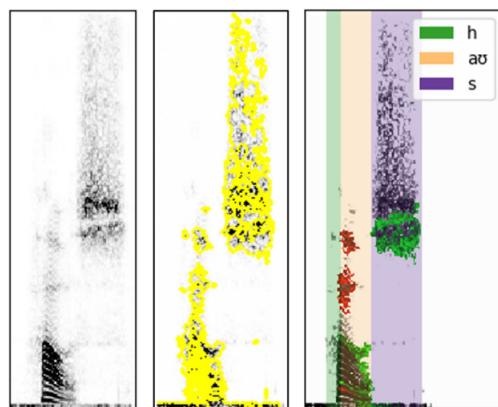


FIGURE 15: A spectrogram of an audio sample (left), its segmentation into superpixels (center) and the output for the user containing LIME visualizations and additional phoneme information (right) [74]

IX. XAI AND MULTIMODAL DATA

Some time input data may differ from conventional input data like audio, video, text, and image. If data is in CSV format, it requires different pre-processing of data and normalization. For example, in industry sensor data are calibrated in CSV datasheets.

In industrial automation, maintenance is one of the crucial aspects for the continuity of industry. Due to various physical parameters like temperature, vibration, pressure, RPM, etc., there are significant impacts on various parts of the assembly line or mechanical system which leads to failure [75]. XAI along with failure diagnosis makes the ML model more transparent and interpretable towards the provided diagnosis of the failed component [76].

In the aviation sector, aircraft maintenance is handled by scheduled or event-based triggered maintenance. Such sort of maintenance is unreliable because that causes serious disaster when aircraft is in the air. Such disasters can be prevented if predictive maintenance is applied. In any giant mechanical system, there is a gradual degradation in the reading of various tools or sensors, these tools are making a cumulative effect for final break down [77]. Such calibration of readings can be used as a feature set and model training is possible for failure diagnosis and remaining useful life (RUL) prediction of aircraft or any critical electro-mechanical system.

The prediction of failure with explanation makes the justification for derived diagnosis. Hence it improves reliability and saves cost [67].

Maintenance with interpretability for failure diagnosis can add useful insights about the disposal of certain parts which might not be available with crew members of maintenance teams. The pipeline of predictive maintenance with XAI insights is mentioned in Fig. 16. of sequential steps like data collection, data cleaning, feature selection, diagnosis, and explanation with validation. One advantage of predictive maintenance it helps to mandatory understanding of different physical components and their physical properties.

X. CONCLUSION

It is emphasized here that XAI is an important and mandatory aspect of AI/ML based application to use in real time. Our study has started discussion from conventional AI and limitations. The need for XAI is well explained in the case of studies along with key issues of explainable AI.

Objectives and scopes of XAI are discussed in length and breadth. We discussed major objectives like transparency, fairness, bias, and confidence. Scope of XAI is discussed in detail for its application in the major domain like NLP, medical, defense and Engineering.

Different methodologies (post hoc and transparent) for explainability are discussed to get preliminary hands on to dive into this field. Conceptual and detailed explanations with the example for all methodologies are also discussed. After providing a conceptual understanding of XAI approaches, we have provided XAI as a tool to be applied to specific kinds of data like image, text, video, audio, and multimodal data.

This survey elaborates a conceptual understanding of XAI along with the importance of explainability that motivates researchers for diversified aspects of XAI. This purpose motivates researchers for interpretable AI/ML methods. These detailed highlights make a baseline for the understanding of the current literature of XAI, which can be approached in two ways. 1) Transparent ML models which are interpretable to an extent by themselves only. 2) Post hoc methods for explainability which makes the model more interpretable. We presented XAI as a tool for responsible AI, a paradigm that can enable series of algorithms that will work in synergy to achieve the goal of responsible AI. Responsible AI stands for trust, confidence, fairness, and transparency.

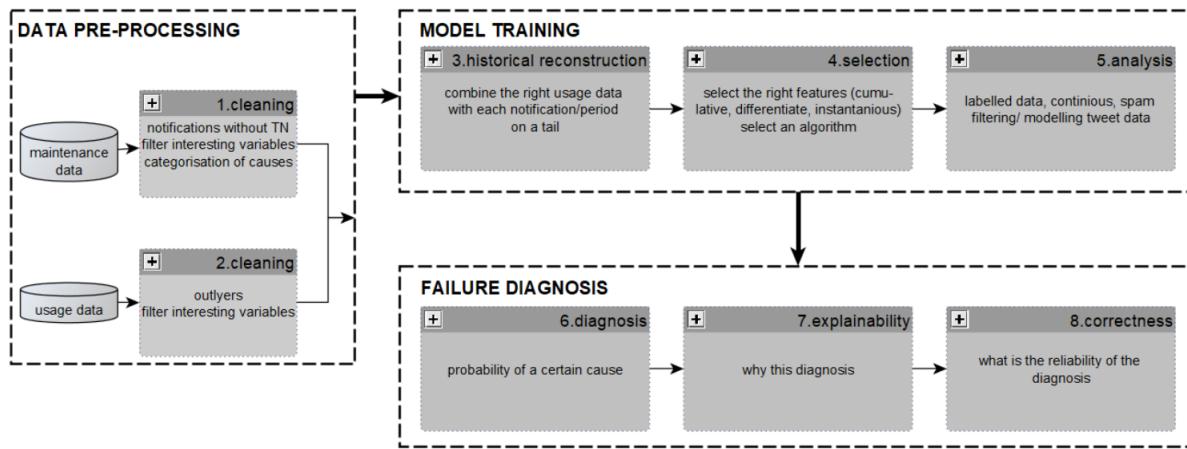


FIGURE 16: Functional diagram of an automated failure diagnosis model [67]

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