Proceedings of the 5th Indian International Conference on Industrial Engineering and Operations Management, Vellore, Tamil Nadu, India, November 6-8, 2025

Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/IN05.20250366
Published: November 6, 2025

A Comprehensive Review on the Applications of Explainable Artificial Intelligence in Healthcare, Agriculture, and Beyond

Ayesha Fatima and Saheba Aijaz
Student, Stanley College of Engineering & Technology for Women
Hyderabad, India
ayeshafatimaNMEIS@gmail.com, sahebaa05@gmail.com

S.M. Hasanuddin
Student, Methodist College of Engineering and Technology, Hyderabad, India
s.hasanuddin20@gmail.com

Umaira Shahneen
Student, Faculty of Engineering, Sharnbasva University, Kalaburagi, India
umairashahneenkhan@gmail.com

Syeda Afifa Fatima
Student, PDA College of Engineering, Kalaburagi, Karnataka, India
safkhadri6@gmail.com

Qutubuddin Syed Mohammed
Professor, Industrial & Production Engineering
P.D.A. College of Engineering, Kalaburagi, India
syedqutub16@gmail.com

Abstract

There are many advancements and applications of AI technology in various fields. The "black box" nature of AI models is something to look into, as it has raised concerns of accountability, and trust in important sectors such as healthcare, plant pathology, agriculture, and finance. Agriculture serves as the foundation of the world economy, which is due to increasing pressure from population growth and environmental and resource constraints. Agriculture and healthcare domains are rapidly changing due to Artificial Intelligence (AI), which is improving disease detection, and other practices. Few of the Deep Learning techniques that have shown an ability to predict successfully are Generative Adversarial Networks, Recurrent Neural Networks, and Convolutional Neural Networks. However, these methods are difficult to implement practically due to their high complexity. Within agricultural and healthcare contexts, Explainable AI (XAI) helps inform users and decisions through transparency, without compromising performance. This paper is an exploration of XAI to understand how it increasing the interpretability and transparency of static models. It will also focus on the various applications of XAI, its challenges, approaches, and the different explainability methods, including LIME, SHAP, and Grad-CAM.

Keywords
Artificial Intelligence, Explainable AI, LIME, Machine Learning Models, Grad-CAM, Plant disease, SHAP, XAI

1. Introduction
Artificial Intelligence is all about enabling machines, computers, and devices to replicate how humans think, behave and make decisions. It is a self-reliant technology that helps in problem solving, without the need for us to step in. The use of AI has grown exponentially over the past few years. It is being implemented in every other sector we can think of. It supports the doctors by detecting and diagnosing diseases in the healthcare domain (Nie et.al.2015), helps banks in decision making for loan approval (Chong et.al. 2017, Pham and Shen 2017), and much more (Joa and Guan 2021, Markus et.al. 2020).

Due to the ongoing and perpetual development of machine learning algorithms, AI has achieved high perform and speed. In the healthcare domain, AI is most widely used for medical imaging (Nazar et.al.2021). But the deep learning algorithms are not trustworthy and are not transparent. These characteristics makes the doctors hesitant about the results of the model. These types of AI models which do not provide human understanding are known as black box models (Von 2021). To improve trust in the results of AI models, various research aims to implement various techniques (Devlin et.al. 2018).

1.1 Objectives
The primary objective of this paper is to discuss the various uses and applications of explainable AI systems in different domains that are sensitive and require transparency and interpretable models. The various sectors that will be covered in this paper are healthcare, agriculture with IOT, geohazards, energy and power. Furthermore, in the following sections, the white box and black box AI models will be discussed, major methods of XAI and growth of XAI will be also discussed.

2. White box and Black box AI
While AI mostly learns from data, but also from the environment and its experience over time (Cole and Eda). AI being the super set contains Machine Learning as its subsets, which further consists of Deep learning. Deep learning algorithms are made up of multiple layers. In contrast the regular ML models, the Deep Neural Networks have numerous hidden layers, due to which large and complex processing of data is possible. These algorithms utilize Neural Networks, where every layer in the network has thousands of neurons. The neuron is a function made to replicate how the human brain works. Even though it is able to provide multiple benefits over traditional models, there is the problem of black box that also comes along with it. The main issue with the black box systems is the absence of clarity and transparency of its internal working. The human users are unaware of how the model made a particular decision which makes it very difficult for them to understand the models' working process. Moreover, there can be security issues, bias introduced in the model, absence of trust and flexibility in models (Rahul and Kinza).

The input data of the black box models can be exploited and manipulated when people who are not authorized get access to it. This can result in wrong and unsafe results. This can occur when proper security protocols are not followed which results in security loop holes. Thus, these models are not to be used with private or sensitive information. These models are prone to bias, and bias in algorithms can come due to the imbalance and errors in the training datasets, further, verifying the decisions or outputs of these models is difficult. As mentioned before, when black box models are used, there is the absence of trust and transparency, due to which the end users or even the developers cannot fully understand the reasoning behind the models results. Without understanding, these results and decisions cannot be fully trusted. Also, these models are neither adaptable nor flexible, which means a model created for one problem or use case cannot be used for another use case, and to do so it would require a great deal of rework.

With the major advancements in AI over time, the other category of systems that was developed is white box AI systems which is also called as explainable AI or XAI. As the name suggests, white box AI system or approach is the opposite to black box AI. It also overcomes the various disadvantages of the black box systems. To overcome the problems of the black box models certain rules have been given for using and building AI that is trustworthy and safe to use. The goal of XAI methods is to build ML models such that there is a balance of interpretability and accuracy. This is done either by building white box ML models or using black box models with a certain level of interpretability. Making AI systems more understandable and transparent to humans such that the performance is not compromised is the main aim of XAI (Gunning 2019, Adadi and Berrada 2018).

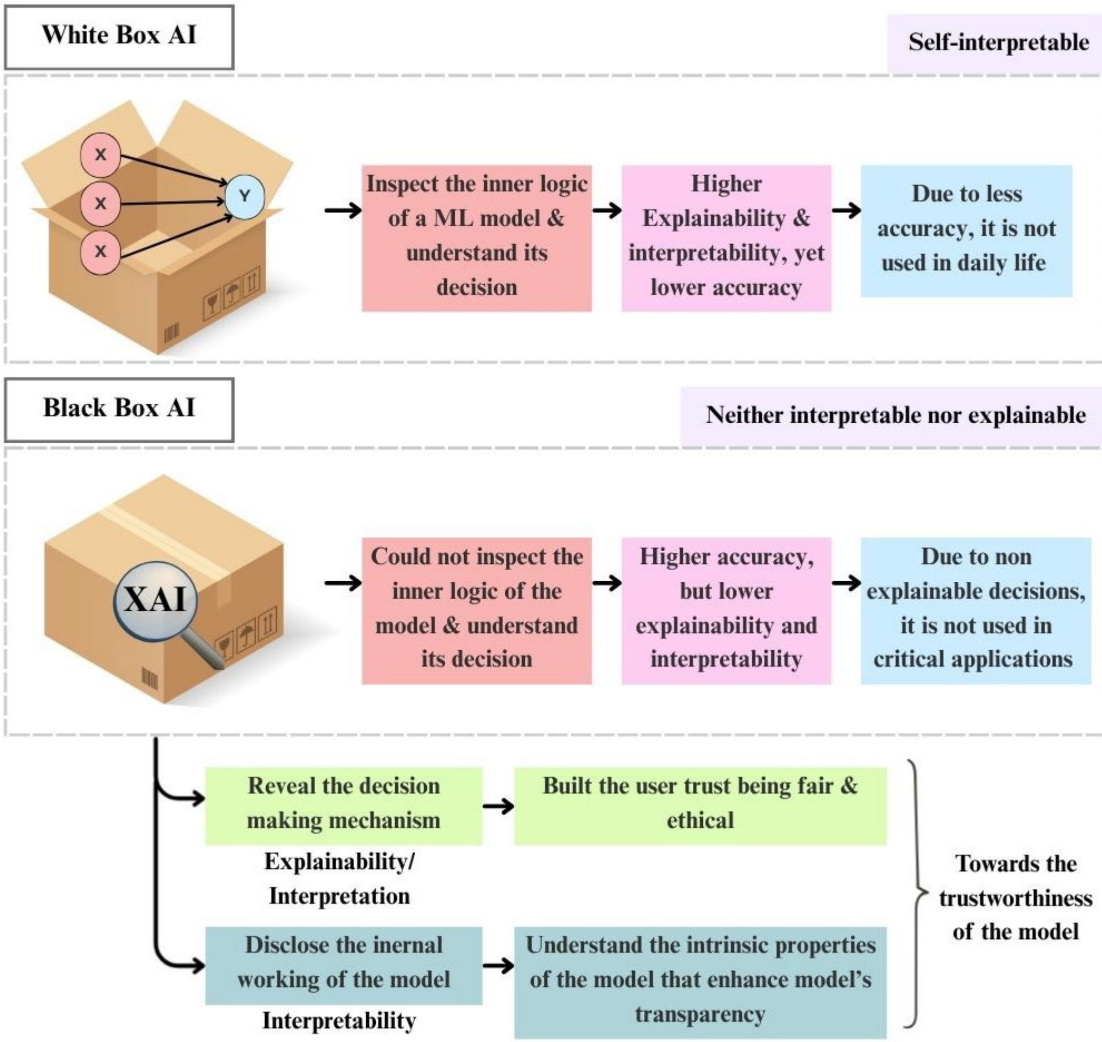

Figure 1. A comparison of white-box and black-box AI models.

As seen in Figure 1, the differences between the two types of AI models are highlighted. Where the white-box AI models are interpretable which makes their outputs and results easily understandable to humans however they are also less accurate. On the other hand, the black-box AI models are having more accuracy but they are less interpretable. To create trustworthy AI models there is a need of complex XAI techniques.

The terms explainability and interpretability and the various other terms that are related to it are transparency, fairness, robustness and responsibility. All of these are used to increase the trust in the model. Explainability is the method of showing the users how inputs and outputs are linked. It helps us understand the reasons of how and why AI models made the particular decisions. The capacity to make automatic interpretations and describe the inner workings of an AI system in human terms is referred to as explainability. Where interpretability helps in revealing the intrinsic properties of a model, the intrinsic model techniques are those that are able to describe the internal working of an AI model in a human understandable form. (Adadi and Berrada 2018, Li et.al.2022, Das and Rad 2020).

3. Growth and Developments in XAI

It is becoming a necessity for humans to understand and stimulate how an AI model arrives at a decision. Especially when AI is developing at such a fast rate. The internal transformations of data and the mathematical computational process is hidden, hence the name black box. The US Defense Advanced Research Projects Agency has defined XAI as an AI technology that can express its logic to a human user, identify its strengths and limits, and impart knowledge of how it could perform in the future (Guidotti et.al.2019). In most of the non-public and industrial AI/ML systems that use DL and ML approaches require even more transparent systems that can explain their output/decisions.

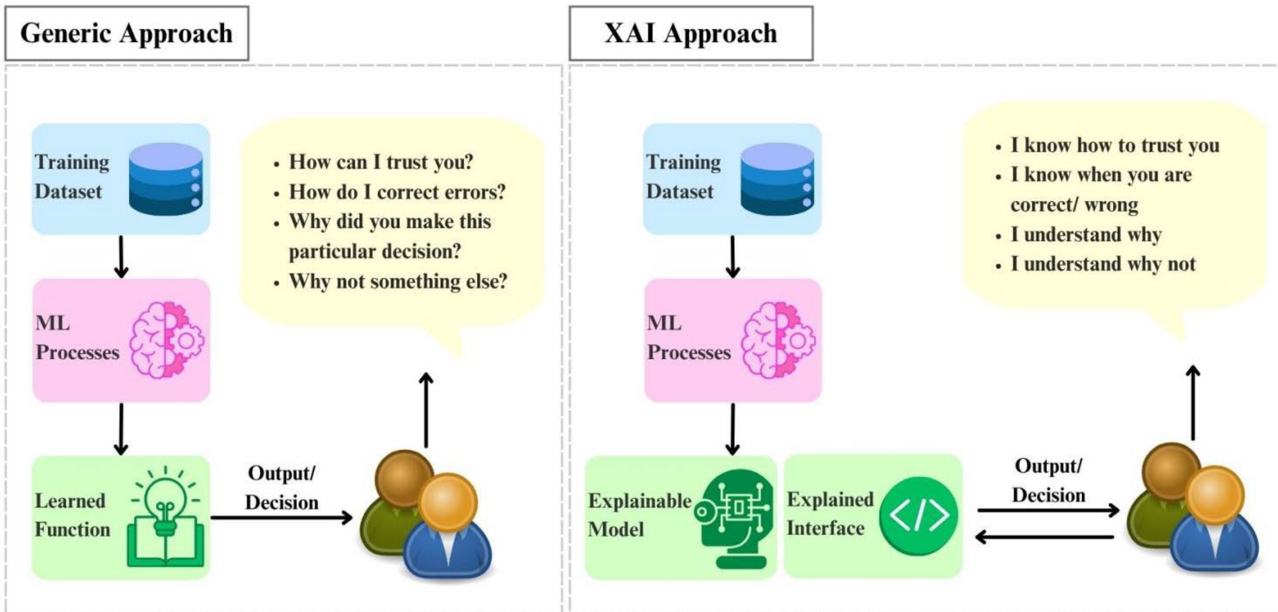

Figure 2. Generic approach and XAI approach

To build such systems that are reliable and understandable requires explainability. In Figure 2, the generic approach is the AI models that is currently used and also the XAI approach is the AI that is expected to be used in the future. The non-linearity in models makes it black boxes. This makes understanding operational and computational processes difficult (Guidotti et.al.2019). This may lead to various issues and hinder the future AI development. It is very difficult to prevent and control irregular behavior in black box models. In critical situations like a medical diagnostic the inference can be disastrous and even fatal.

The explainability of AI models is necessary to address these challenges, as it is the ability to get the understanding of the mechanisms behind model. The relation between the reliability and predictive accuracy of an AI model is such that when the predictive accuracy is higher, then the model is less explainable (Xu et.al.2019). This shows that these both characteristics are inversely proportional to each other. One of the types of research illustrates the same correlation, where it was seen that Support Vector Machines, ensemble models, and decision trees have the highest explainability levels, however they also have the poorest performance in terms of predictive accuracy (https://gdpr.eu/what-is-gdpr/, 2019). Whereas, DNNs are least explainable but also have the highest predicting performance and accuracy out of any other machine learning technique.

4. Literature Review

There are abundant applications of XAI in several domains, some of which will be covered in this section. Based on the literature published in recent years, there are many areas which have utilized the benefits of XAI. Few of which are healthcare, agriculture with IOT, geohazards, energy and power. In one of the recent research papers, the development and evaluation of an Explainable Artificial Intelligence (XAI) model based on deep learning for medical image classification was discussed. The authors used convolutional neural network (CNN) to classify Chest X-Ray (CXR) images. This was done for both binary classifications to classify the images into COVID-19 and normal. Further they used it for multiclass classification of COVID-19, pneumonia and normal. They specifically used the

VGG16 model and combined it with the LIME, an XAI method. This method was used to give local explanations for each individual prediction. LIME gives visually explanations through heatmaps, by highlighting the key lung areas of the lungs in the CXR images that were responsible for model's decision. This model achieved a testing accuracy of 90.6% (Ghnemat et.al.2023).

Another study also proposed a CNN model for classifying CXR images, however they focused on four categories: COVID-19, Pneumonia, Tuberculosis (TB), and Normal. The model was trained and validated on a dataset containing 7,132 chest X-Ray images. The authors were able to achieve an accuracy of 94.54% on validation dataset. Further to improve interpretability, they used three XAI methods, namely, SHAP, LIME, and Grad-CAM, which highlighted the important regions in the image regions (Bhandari et.al. 2022). This added an advantage of explainability. Medical experts confirmed these explanations, which shows the model's clinical relevance. The model shows strong sensitivity and specificity across all classes and is suitable for deployment in low-resource settings.

Syed Mohammed et.al. (2023) proposed a Convolutional Neural Networks (CNN) based advanced system to detect arecanut crop disease in leaves, trunk and fruit. The paper discusses the processing input images, assigning learnable weights and biases to different elements within the images, and then learning from these patterns to differentiate healthy plants from diseased arecanut plants. A CNN model was developed and evaluated the CNN model, to use datasets from published literature, which contains a diverse range of images depicting both healthy and diseased arecanut plant samples.
Shahneen Umaira et.al 2024 conducted a study on Detecting Manipulated Visuals using AI. The paper discusses on image forgery, image splicing and copy-move forgery. The application of machine learning and deep learning like Support Vector Machines (SVM) and CNN models used to detect forgery. The evaluation of techniques in distinguishing authentic images from forged images and their effectiveness is discussed.

The study published in 2023, used Explainable AI techniques to improve the interpretability and trustworthiness of their MS-CNN model (Sarkar et.al.2023). They used SHAP and Grad-CAM techniques. Where SHAP stands for SHapley Additive exPlanations, the SHAP values measure the contribution of each pixel to the model's output, showing regions that positively or negatively affect the prediction for each class. For instance, in lung opacity cases, SHAP visualizations show how various parts of the lung contribute to classifying the image as lung opacity or COVID-19. This hepls in understanding how the model makes decisions. Also, Grad-CAM generates heatmaps from the final convolutional layers, it visually shows the areas of the chest X-ray that the model focuses on when identifying diseases such as fibrosis or tuberculosis. These heatmaps are put over the original images so that affected regions van be noticed easily. This also provided doctors with explanations which are easy to understand because it uses visuals.

For prediction of cardiovascular disease, a study proposed an XAI framework that used ensemble classification techniques. Authors used a dataset containing 303 instances and 14 features. Support vector machines (SVM), AdaBoost, K-nearest neighbor (KNN), bagging, logistic regression (LR), and naive Bayes, were implemented within the XAI framework. The authors used feature and explainable feature weight initialization, normalization, and optimization to improve the performance and interpretability of the models. SVM, logistic regression, and naive Bayes achieved the highest accuracy of around 82% to 89% (Guleria et.al.2022). For further explanations of the effect of individual features on the outputs, SHAP was used. It was seen that the features ‘sex’ and ‘age’ were the most impactful features to predict if a patient will have heart diseases. This XAI based ensemble classifiers showed higher interpretability compared to conventional models.

Another study by Kamran Kafeel et.al.2024 analyzes the potential risk factors of heart diseases and potential prediction models based on 303 records of patients and 14 attributes. Exploratory data analysis (EDA) is used to get basic insights. Ten algorithms like logistic regression, Decision trees, Random Forest, LDA, QDA, Neural Networks etc. are applied. Other enhanced classifiers like CatBoost, XGBoost and LightGBM are also considered. The intensive data analysis helps create reliable prognosis and understanding of risk factors that lead to heart diseases. Enchanced diagnosis and prevention.

These studies emphasize the need for interpretability and trustworthiness in AI models, especially when used in healthcare for clinical decision-making. The use of XAI in healthcare helped to generate interpretable visual explanations that work well with radiological findings and professional opinions. This transparency of AI models is essential because it help in the integration between AI and human experts. The XAI methods help simplify the model's behavior. Further it helps in identifying possible misclassifications. All of this leads to an increase in clinical confidence in the use of AI models for automatic diagnosis process.

To discuss the uses of XAI in agriculture, one paper used EfficientNetV2L, MobileNetV2, and ResNet152V2 models for the detection of 38 types of leaf diseases across 14 different plants. Where EfficientNetV2L performed best by achieving an accuracy of 99.63% on the test set (Mehedi et.al.2022). The authors implemented the LIME framework, which stands for Locally Interpretable Model Agnostic Explanations. To explain how XAI was helpful in detecting plant leaf diseases using LIME visualizations consider the case of diseased leaves such as Cherry Bacteria Spot. LIME showed that the model focuses on the affected areas of the leaves which show symptoms of disease, and the model doesn't focus on the irrelevant background regions. This localized explanation generated using LIME confirms that the decisions of the model is only due to the meaningful features that are related to the disease. This increases trust and confidence in the model, showing that it is reliable.

XAI is useful in agriculture because it provides understanding of the AI model's outputs, which is important for when these models are used by farmers because they need to develop trust in automated systems. XAI helps by clearly explaining why a model classifies a plant or plant leaf as diseased. This interpretability of models reduces the misdiagnosis and helps in early detection of diseases to minimize crop loss and maximize agricultural produce.

An IoT based system called Vital was developed for automatic irrigation in fields. The system used wireless devices, IoT gateways, a scalable big data platform called Cenote, a web interface, and a fuzzy rule-based system. This fuzzy rule-based system (FRBS) automates irrigation decisions based on sensor data. The highlight of Vital is that it used explainable AI through a Mamdani-type fuzzy rule-based system (Nikoloas et.al.2020). This XAI system makes decisions of when to irrigate the field using linguistic rules and fuzzy logic that are interpretable. This also allows expert knowledge to be used directly and makes the system transparent and trustworthy. The FRBS continuously monitors sensor data and calculates parameters like soil moisture and crop evapotranspiration, and based on the data it automatically executes the irrigation commands. Vital was successfully evaluated in the automatic irrigation of an olive tree farm. Results showed that the FRBS was able to match theoretical irrigation needs. This system showed better efficiency and outperformed the manual water control. Further, the explainability, low operational cost, and adaptability of this system makes it a promising tool for smart irrigation in agriculture.

XAI is increasingly being used in energy and power system domains. Specifically, it is used in critical power grid applications, energy sector applications including renewable energy forecasting, and building energy management. For power grid stability assessment, XAI methods explain model predictions for the transient stability and frequency deviations. This helps the operators to understand the behaviors of critical systems and also to take preventive actions. Also, in fault diagnosis, XAI helps in identifying which features in the data contributed most to classifying transformer faults. This improves the fault detection accuracy (Han et.al.2019) (Machlev et.al.2022). In renewable energy forecasting, XAI methods provide insights that improve the accuracy of photovoltaic power generation models and also improves the solar irradiance predictions (Kruse, Schafer and Witthaut 2021).

In the management of energy in a building XAI is used to forecast or predict the energy consumption. This helps in promoting different ways the consumers can save energy. Techniques like SHAP explain the effect of various inputs on cooling load predictions and energy benchmarking. This way transparent insights into model decisions can be obtained. Overall, XAI improves the interpretability of ML models in energy and power system applications, it also helps build confidence and trust between the users like the grid operators and end consumers. This helps support the implementation of AI in these critical sectors (Kruse, Schafer and Witthaut 2021), (Zhang, Xu and Xhang 2020).

A geohazard is a geological process that can cause damage to property and life. Examples of geohazards are landslides, earthquakes, tsunamis, and volcanoes. XAI helps in this domain by providing transparency and interpretability, which is essential for gaining trust for the decision making in disaster risk management. In one study the authors developed a landslide susceptibility model using CNN, particularly for the CheongJu region in South Korea. The authors used SHAP summary plots with the DeepExplainer variant, dependence plots, and force plots to identify the various factors that help determine if landslide will occur or not. This made the model's decision process easy to understand. The SHAP plots showed that occurrence of landslide is negatively correlated with altitude however, it is positively correlated with the slope. Without XAI, these insights are difficult to extract from traditional ML outputs. The authors also discussed that future landslide studies that uses ML should also include explainability so that the model is transferable and trustworthy and can effectively support mitigation (Biswajeet et.al.2023).

5. Conclusion

The goal of this review paper was to highlight the significance, development, and uses of Explainable Artificial Intelligence (XAI) in important fields like healthcare, agriculture, energy, and geohazards. It is clear thorough analysis of numerous studies that XAI is essential to improving the transparency, interpretability, and reliability of deep learning and complex AI models.

In healthcare, XAI methods such as LIME, SHAP, and Grad-CAM have turned confusing black-box diagnostic systems into a trustable tool for clinical decisions. These models provide explanations visually and statistically to explain the AI predictions with medical reasoning, and provide interpretability. In agriculture, the development of XAI based algorithms for plant disease identification, and IoT based smart irrigation systems, shows how XAI improves trust among farmers and helps to make better decisions to improve agricultural sustainability. Additionally, in energy and power, XAI methods provides operators with an understanding of AI predictions regarding grid reliability, energy management and renewable forecasts to improve safety and reliability. Lastly, explainable frameworks that can offer interpretable explanations can be used to make disaster mitigation decisions in geohazards. It is also noted in this review that improving predictive accuracy comes at the expense of interpretability, and XAI methods are being developed to gain the best of both worlds that is high performing models that are understandable for the user.

To summarize, this paper has provided a detailed insight into how XAI is transforming important areas by building trust, accountability, and transparency between humans and AI. This review has analysed XAI's multiple applications and challenges of real-life implementations. This discussion has also contributed to our understanding of the future of AI, as we transition to an era where AI does not only produce high degrees of accuracy, rather will also be systems that humans can interpret, trust, and rely on.

References

Adadi, M. Berrada, Peeking inside the black-box: a survey on explainable artificial intelligence (XAI), IEEE Access 6, 52138–52160, 2018

Das, P. Rad, Opportunities and challenges in Explainable Artificial Intelligence (XAI): A survey, arXiv preprint arXiv:2006.11371, 2020

Markus, J. A. Kors, and P. R. Rijnbeek, ''The role of explainability in creating trustworthy artificial intelligence for health care: A comprehensive survey of the terminology, design choices, and evaluation strategies", Journal of Biomedical Informatics. 113. 103655. 10.1016/j.jbi.2020.103655, 2020

Biswajeet Pradhan, Abhirup Dikshit, Saro Lee, Hyesu Kim, An explainable AI (XAI) model for landslide susceptibility modeling,Applied Soft Computing,Volume 142,2023,110324,ISSN 1568-4946, https://doi./10.1016/j.asoc.2023.110324

Cole Stryker, Eda Kavlakoglu,"What is artificial intelligence (AI)?", ibm.com, https://www.ibm.com/think/topics/artificial-intelligence (accessed October 15, 2025)

Devlin, J.; Chang, M.; Lee, K.; Toutanova, K. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding., arXiv:1810.04805, 2018

Gunning, M. Stefik, J. Choi, T. Miller, S. Stumpf, G.-Z. Yang, XAI: Explainable artificial intelligence, Science Robotics 4 (37) http://dx.doi.org/10.1126/scirobotics.aay7120, 2019

Chong, C. Han, F.C. Park, Deep learning networks for stock market analysis and prediction: Methodology, data representations, and case studies, Expert Syst. Appl. 83, 187–205, 2017

Joa and C. Guan, ''A survey on explainable artificial intelligence (XAI): Toward medical XAI,'' IEEE Trans. Neural Netw. Learn. Syst., vol. 32, no. 11, pp. 4793–4813, Nov. 2021.

Xu, H. Uszkoreit, Y. Du, W. Fan, D. Zhao, and J. Zhu, ''Explainable AI: A brief survey on history, research areas, approaches and challenges,'' in Proc. CCF Int. Conf. Natural Lang. Process. Chin. Comput., pp. 563–574, 2019

Ghnemat, R.; Alodibat, S.,Abu Al-Haija, Q. Explainable Artificial Intelligence (XAI) for Deep Learning Based Medical Imaging Classification. J. Imaging 2023, 9, 177. https://doi.org/10.3390/ jimaging9090177

Guleria, P.; Naga Srinivasu, P.; Ahmed, S.; Almusallam, N.; Alarfaj, F.K. XAI Framework for Cardiovascular Disease Prediction Using Classification Techniques. Electronics 2022, 11, 4086. https://doi.org/10.3390/electronics11244086

Han T, Chen J, Wang L, Cai Y, Wang C. Interpretation of stability assessment machine learning models based on Shapley value. In: 2019 IEEE 3rd conference on energy internet and energy system integration. p. 243–47,.2019

Is GDPR, the EU's New Data Protection Law? [Online]. Available:https://gdpr.eu/what-is-gdpr/, 2019

Kruse J, Schäfer B, Witthaut D. Revealing drivers and risks for power grid frequency stability with explainable AI. Patterns 2021;2(11):1–26.

Kamran, kafeel, Umaira Shahneen, Fazeel Afwan Ahmed, Hasanuddin S M, and Ayesha Fatima. "Cardiovascular Disease (CVD) Analysis using Gradient Boosting Algorithms like CatBoost, LightGBM.." In *4th Indian International Conference on Industrial Engineering and Operations Management*. 2024, https://doi.org/10.46254/IN04.20240161.

Kruse J, Schäfer B, Witthaut D. Exploring deterministic frequency deviations with explainable ai. In: 2021 IEEE international conference on communications, control, and computing technologies for smart grids. SmartGridComm, IEEE; 2021, p. 133–9.

Nie, M. Wang, L. Zhang, S. Yan, B. Zhang, T.-S. Chua, Disease inference from health-related questions via sparse deep learning, IEEE Trans. Knowl. Data Eng. 27 (8) 2107–2119, 2015

Mohan Bhandari, Tej Bahadur Shahi, Birat Siku, Arjun Neupane,Explanatory classification of CXR images into COVID-19, Pneumonia and Tuberculosis using deep learning and XAI,Computers in Biology and Medicine,Volume 150,2022,106156,ISSN 0010-4825,https://doi.org/10.1016/j.compbiomed.2022.106156

Mehedi et al., "Plant Leaf Disease Detection using Transfer Learning and Explainable AI," 2022 IEEE 13th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON), Vancouver, BC, Canada, 2022, pp. 0166-0170, doi: 10.1109/IEMCON56893.2022.9946513

Nazar, M.; Alam, M.M.; Yafi, E.; Mazliham, M. A systematic review of human-computer interaction and explainable artificial intelligence in healthcare with artificial intelligence techniques. IEEE Access, 9, 153316–153348, 2021

Nikolaos L. Tsakiridis, Themistoklis Diamantopoulos, Andreas L. Symeonidis, John B. Theocharis, Athanasios Iossifides, et al.. Versatile Internet of Things for Agriculture: An eXplainable AI Approach. 16th IFIP International Conference on Artificial Intelligence Applications and Innovations (AIAI), Jun 2020, Neos Marmaras, Greece. pp.180-191,10.1007/978-3-030-49186-4_16

Rahul Awati, Kinza Yasar, "What is black box AI?", techtarget.com, https://www.techtarget.com/whatis/definition/black-box-AI (accessed October 15, 2025)

Guidotti, A. Monreale, S. Ruggieri, F. Turini, F. Giannotti, and D. Pedreschi, ''A survey of methods for explaining black box models,'' ACM Comput. Surv., vol. 51, no. 5, pp. 1–42, doi:10.1145/3236009, 2019

Machlev, L. Heistrene, M. Perl, K.Y. Levy, J. Belikov, S. Mannor, Y. Levron,Explainable Artificial Intelligence (XAI) techniques for energy and power systems: Review, challenges and opportunities,Energy and AI,Volume 9,2022,100169,ISSN 2666-5468, https://doi.org/10.1016/j.egyai.2022.100169 .

Syed Mohammed, Q., Mahveen N., Shahneen U., S M H., Fatima A., and Aijaz S., Enhancing Arecanut Plant Wellness: Innovative Disease Detection using Deep Learning Algorithms, *Proceedings of the 3rd Indian International Conference on Industrial Engineering and Operations Management*, https://doi.org/10.46254/IN03.20230109 .

Sarkar, O.; Islam, M.R., Syfullah, M.K.; Islam, M.T.; Ahamed, M.F.; Ahsan, M.; Haider, J. Multi-Scale CNN: An Explainable AI-Integrated Unique Deep Learning Framework for Lung-Affected Disease Classification. Technologies 2023, 11, 134. https://doi.org/ 10.3390/technologies11050134

Shahneen, Umaira, kafeel kamran, Hasanuddin S M, Ayesha Fatima, Saheba Aijaz, and Qutubuddin Syed Mohammed. "Detecting Manipulated Visuals with AI." In *4th Indian International Conference on Industrial Engineering and Operations Management*. 2024, https://doi.org/10.46254/IN04.20240145

Pham, Y. Shen, A deep causal inference approach to measuring the effects of forming group loans in online non-profit microfinance platform, arXiv preprint arXiv:1706.02795, 2017

Von Eschenbach, W.J. Transparency and the black box problem: Why we do not trust AI. Philos. Technol. , 34, 1607–1622, 2021

X. Li, H. Xiong, X. Li, X. Wu, X. Zhang, J. Liu, J. Bian, D. Dou, Interpretable deep learning: interpretation, interpretability, trustworthiness, and beyond, Knowledge and Information Systems 64 (12), 3197–3234, 2022

Zhang K, Xu P, Zhang J. Explainable AI in deep reinforcement learning models: A SHAP method applied in power system emergency control. In: 2020 IEEE 4th conference on energy internet and energy system integration. 2020, p. 711–6. http://dx.doi.org/10.1109/EI250167.2020.9347147.