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TOWARDS TRUSTWORTHY TELEMEDICINE: APPLYING EXPLAINABLE AI FOR REMOTE HEALTHCARE RECOMMENDATIONS

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ABSTRACT

In the rapidly evolving landscape of healthcare, telemedicine has emerged as a pivotal tool, offering patients remote access to medical consultations and treatments. However, the trustworthiness of telemedicine platforms remains a concern, especially when artificial intelligence (AI) is employed to provide healthcare recommendations. This research paper delves into the application of Explainable AI (XAI) in telemedicine to enhance its trustworthiness and transparency. We investigate the current challenges faced by telemedicine platforms, particularly in the context of AI-driven recommendations, and explore how XAI can address these issues by offering clear, understandable explanations for AI-generated outputs. Our findings indicate that integrating XAI into telemedicine not only bolsters patient trust but also empowers healthcare professionals to make more informed decisions based on AI recommendations. We conclude by proposing a framework for the seamless integration of XAI in telemedicine platforms and discuss its potential implications for the future of remote healthcare.

Keywords: Explainable AI (XAI), Trustworthiness, Remote Healthcare, Deep learning

1. INTRODCUTION

Artificial intelligence (AI) is a method that refers to a system or a machine that imitates human intelligence to perform functions in the real world. AI allows the system to be trained from the data and to think and learn from the experience to solve particular problems. It can heuristically refine itself based on the data used. AI applications include advanced web Search Engines, Automated Driving Cars, Games, Human Speech Recognition, Recommendation System, Healthcare etc.

AI was developed around 1950 in the computer science sector, and it copied the human mind to develop machines that can process, methodise, and perform based on the data given to the system, which will be useful when large amounts of datasets are used [1]. AI machineries widely being used in the industrial domain and prompted to do a more research works in engineering fields such as NLP (natural language processing), diagnosis of diseases and medicine, science [2]. AI machines used to learn from their previous experiences, which was helpful in solving problems, and it has been used in different application domains to increase the performance of the AI machines [3].

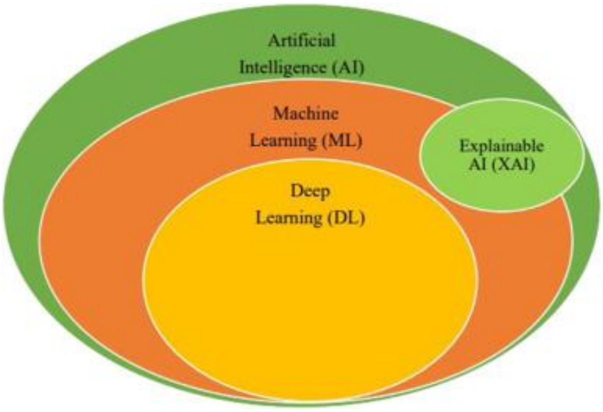

Fig. 1 explains the connection between the Artificial-Intelligence, Machine-Learning, Deep-Learning, and Explainable Artificial- Intelligence.

Machine Learning (ML) is a technique that allows a computer to identify patterns, make predictions that are more accurate, and refine itself via experience without being precisely programmed to do so. Machine Learning is used to build an AI-driven application. This process is done by using the ML Methodologies.

1.1 The process of ML:

The process of ML is described in Fig. 2. AI are used to make the decisions a lot. Integrated with AI, the system can perform tasks faster and predict the decisions needed to solve complex problems, evaluate risks, and evaluate business performance.

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Fig. 2. Process of ML.

To measure the ML model's performance, different metrics have been used based on the ML algorithm used in the application domain. Area under Curve (AUC) and Accuracy under the receiver operating characteristics (AUROC) are the most commonly used performance metrics in ML tasks. AUC represents the performance of the model at separating classes, whereas accuracy denotes the model's overall correctness [1]. ML models have been trained with a larger amount of data and make the most accurate predictions [2]. ML is classified into two main groups: supervised and unsupervised learning. Further, supervised learning is classified as semi-supervised learning [4] and reinforcement learning [5].

1.2 Types of learning methods in ML

Advanced machine learning styles have been explained by Supriya V. Mahadevkar et al. [6]. Some of the learning styles are listed in Fig. 3 [6].

Deep learning (DL) deals with algorithms influenced by the structure and function of the human brain. DL utilises artificial neural networks to create an intelligent model and solve critical problems. DL makes use of both structured and unstructured data to train a model (e.g., visual assistants like Siri, Alexa, and face recognition, etc.). DL is used for medical research and the prediction of life-threatening diseases. Recently, Deep Neural Networks (DNNs) have established remarkable predicting performance [7].

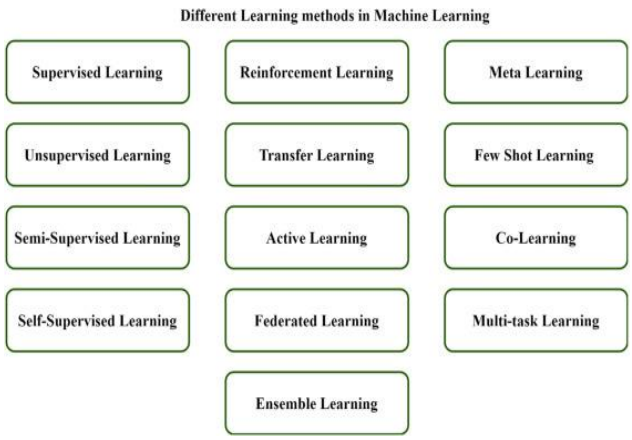

Figure 3 – Different machine learning method

Nowadays, deep learning has made important progress due to its increased range of calculating power and because it provides a better solution for a larger number of datasets [2]. AI has a subclass called Deep Learning (DL) that is created on an artificial neural network. In this DL process, the input data will be trained by themselves over mathematical illustration. Some of the DL models are Convolutional Neural Networks (CNN), Visual Geometric Group Net (VGGNet), Residual Network (ResNet), Fully Convolutional Networks (FCNs), U-net [8], Deep feed forward networks, Siamese Neural Networks, Graph Neural Networks [9]. Deep Learning models are divided into three modules called data pre-processing, feature extraction and recognition, and model optimization [10].

The Artificial Intelligence algorithm was used to make the user take the decision in their business, but humans do not have any knowledge about the output of the AI or how it was reached. So, it is difficult for the users, to understand the output and process of the outcome. Hence, Explainable Artificial Intelligence (XAI) is being used.

Explainable AI (XAI) explains the inner process of a model i.e., used to provide the explanation of the methods, procedures and output of the processes and that should be understandable by the users. The Defense Advanced Research Project Agency (DARPA) invented the term "Explainable AI" (XAI). It will be called as "White box" because of explaining the process of the model. Training data will be given as an input, and based on the requirements or application domain, you will have to select the methodology for the prediction and the XAI techniques being used to explain the inner workings of the models and the output with an explanation interface as mentioned in Fig. 4. Hence, the users had knowledge about the output of Explainable AI, which will increase their trust in AI models.

Based on the knowledge of the output, users can improve the accuracy of the outcome and also expose the flaws in the model, which again will be useful for the users to make the right decision to improve the model. Explainable AI is used in critical sectors like healthcare, signal processing, etc.

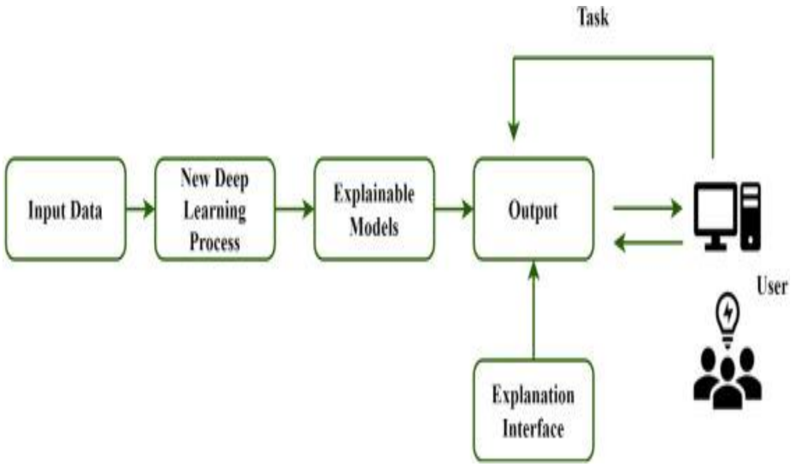

Fig. 4. Process of Explainable AI.

Methods of Explainable AI are being classified into two categories: knowledge-driven and data-driven [11]. Knowledge-driven XAI needs knowledge about the methods to provide the explanation. Data-driven XAI needs local, global, and instance-specific methods for explanation. Most common XAI approaches have been classified based on an explanation of the scope of the model. Linear regression is self-interpretable with simple data called an "intrinsic model" (ex., Logic Analysis of Data (LAD)) and non-linear is interpretable with more complex data called "post-hoc approaches" (ex., Local Interpretable Model-agnostic Explanation and SHapley Additive explanations), "model agnostic", "model specific", "class activation map" (CAM), "layer-wise relevance propagation" (LRP), "gradient weighted CAM", Cluster-based, Filter-based, Attention Mechanism, Rule-Based, Knowledge-Based, Interpretable Model, Auto encoder-Based, Tree-Based [12].

2. MOTIVATIONS

In an era where technology is rapidly advancing and reshaping every facet of our lives, telemedicine stands out as one of the most promising revolutions in healthcare. By allowing patients to access medical expertise regardless of geographical barriers, telemedicine promises a democratization of healthcare services, ensuring that quality care is a right and not a privilege. But as we infuse artificial intelligence into this paradigm, the promise comes with a caveat. While AI has the potential to make diagnoses swift and treatment suggestions more precise, the inherent opacity of its decision-making processes becomes a concern. For telemedicine to be universally accepted and integrated, it is imperative that both medical professionals and patients trust the technology behind it. The challenge isn't merely technical but deeply human. Medicine is an intimate profession, where trust forms the bedrock of the patient-doctor relationship. Introducing AI-driven recommendations adds a layer of complexity to this dynamic. Without understanding the 'why' behind an AI recommendation, how can a doctor explain a diagnosis to a patient? And without such understanding, how can a patient place their trust in a machine's suggestion about their health? The need for Explainable AI in telemedicine isn't just to enhance the technology's efficiency but to ensure that as we progress into a new era of healthcare, we carry forward the essential human elements of trust, understanding, and empathy.

3. STATEMENT OF THE PROBLEM

Telemedicine, while offering unprecedented convenience and accessibility in healthcare delivery, has raised concerns regarding the reliability and transparency of AI-driven medical recommendations. As healthcare decisions significantly impact patient outcomes, there's an urgent need to ensure that AI-generated advice is both accurate and interpretable by healthcare professionals and patients alike. The lack of explainability in current AI models used in telemedicine can lead to mistrust, potential misdiagnoses, and suboptimal patient care. This research seeks to address the pressing challenge of integrating Explainable AI (XAI) into telemedicine platforms to enhance their trustworthiness and ensure that remote healthcare recommendations are not only accurate but also transparent and easily interpretable.

4. OBJECTIVES

4.1 Primary Objectives:

1. Investigate the current trust levels in AI-driven telemedicine among healthcare professionals and patients.

2. Design and create an Explainable AI (XAI) framework tailored for telemedicine applications.
3. Test the XAI framework in real-world scenarios to measure its effectiveness in enhancing trust and understanding.

4.2 Secondary Objectives:

1. Review and analyze the AI models currently implemented in telemedicine platforms.
2. Conduct qualitative interviews with healthcare professionals and patients to understand their perspectives on AI in telemedicine.
3. Develop educational materials to train healthcare professionals about the integrated XAI system.
4. Suggest policy guidelines and best practices for XAI integration into telemedicine.
5. Explore the potential of expanding the XAI framework to other medical technologies and systems.

5. RELATED WORKS

Explains about the growth of development and deployment of XAI in the recent years. Based on the domains, the related articles have been segregated.

5.1. Explainable AI in agriculture

Kaihua Wei, Bojian Chen, et al. [13] explored XAI in the agricultural classification field using DL models to detect Leaf Disease Classification. Five leaves dataset is used. Several categories of dataset have been arranged into 3 experiments such as VGG, GoogLeNet and ResNet models, respectively. In that, ResNet-attention model utilized with 3 interpretable methods and thus it shows result of greatest accuracy rate of 99.11%, 99.4%, and 99.89% in the 3 experiments. Attention module also used to improve the feature extraction and clarify the focus of the model

5.2. Explainable AI in computer vision

Joshi et al. [14] Deep neural networks play an important role in Computers vision, NLP tasks, and many other domains, and researchers have investigated about Multimodal AI with XAI for better interpretability and understanding of the model. Hamad Naeem et al. [15] Inception-v3's CNN-based transfer-learned model is proposed to identify the malware using colour image malware display in Android's (DEX) Dalvik Executable File. Markus Langer et al. [16] explained the XAI concepts from the stakeholders' perspective. Gulsum Alicioglu, Bo Sun [17] Visual analytics been used for the well understanding of neutral networks for the end-users via XAI methods. Dang Minh et al. [18] explain the XAI methods in terms of three groups: pre-modeling explainability, interpretable models, and post-modeling explainability. Savita Walia et al. [19] The ResNet-50 architecture obtained an accuracy of more than 98% with different datasets to detect the manipulation of images. Ahmed Y. Al Hammadi et al. [20] proposed explainable with DL and ML models with EEG signals, used to identify the industrial insider threats.

5.3. Explainable AI in finance

Tanusree De et al. [21] proposed a method with combinations of clustering of the network's hidden layer representation and TREPAN decision tree and UCI Machine-Learning-Repository data sets used to predict the credit card default application. Implemented the methods using python programming language in PyCharm IDE. This method able to create better quality reason codes to make the human to understand the prediction of outcome from the neural network model. Future approach is to implement this method to the other machine learning algorithms.

5.4. Explainable AI in forecasting

Joze M. Rozanec et al. [22] proposed an architecture for the XAI using semantic and AI technologies, and it is used to detect demand forecasting and deployed in the real world. The Knowledge graph is used to provide the explanation about the process of demand forecasting at a higher level of explanation than the specific features. Hence, it is used to hide the sensitive information about the forecasting models used to provide the confidentiality. Their future work is to improve the quality of explanation in the domain of demand forecasting and media events Han-Yun Chen et al. [23] proposed XAI methods for the vibration signal analysis of the CNN model using fault classification. Initially, signals are converted into images using STFT called Short-time Fourier transform then the input is given to the CNN as classification model for the signal analysis with Grad-CAM, then the explanations are verified by using neural networks, adaptive network-based fuzzy inference system (ANFIS) and decision trees

5.5. Explainable AI in the healthcare domain

Health Care data [24] are collected from many different sources. Some data is collected directly from clinical trials and research, and some other data is collected via sensor. DenseNet and Convolution Neural Network (CNN) models have been developed by V. Jahmunah et al. [25] to predict myocardial infarction (MI). An enhanced technique of

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Class Activation Maps (CAM) called Gradient-weighted CAM is used to visualize the productivity of the classification task for both models. This approach had the potential to diagnose MI in hospitals. AI and ML play a vital role in the health care domain. To gain the trust of AI models, XAI is used. It will bring the trust in the predictive modelling on the practical situation [24]. Jaishree Meena et al. [26] done the investigation about skin cancers of non-melanoma skin cancers for both the men and women. The Python SHAP (SHapley Additive exPlanations) programming language has been used on trained XGboost ML models for identifying the biomarkers for predicting skin cancers. Miquel Miro-Nicolau et al. [27] investigated the X-ray-image-related task using Explainable AI. Class Activation Maps (CAM) have been used to represent X-ray images. Lombardi, A. et al. [28] have investigated to predict the AD called as Alzheimer's-Disease and cognitive impairment with XAI. The ADNIMERGE R package and Random Forest Classifiers have been used to predict the disease.

Chang Hu et al. [29] proposed a ML model for the readmission of a septic patient in the Intensive Care Unit and SHAP values used to extract the related features which are used for accurate prediction and LIME used to explain about the models. Djordje Slijepcevic et al. [30] developed a Layer-wise Relevance Propagation method with XAI to analyse the clinical gait on a time series. They introduced XAI for the time series classification and will promote in future to detect the clinical gait for the accurate prediction. Jeremy Petch et al. [31] have been given information about the concepts and techniques of XAI in the field of cardiology. Nor et al. [32] explain the XAI in the fields of medicine, psychology, clinical traits, and others. Prognostics and Health Management (PHM), however, failed to provide the analytical process of how XAI works in PHM. XAI used to provide knowledge about the diagnosis and detection of abnormal activities. Marwa Obayya et al. [33] proposed XAI methods in the field of teleophthalmology to reduce the waiting time of the patients, improve the services, increase accuracy, increase speed, and increase productivity in the field of telehealth. Using classification model, obtained 98.24% of accuracy. Nikolaos I. Papandrianos et al. [34] developed a deep XAI method used to predict CAD (coronary artery disease) by using the SPECT MPI images. David Pertzborn et al. [35] proposed a deep learning model for the detection of cancers. Using a deep learning model, researchers obtained 80% greater accuracy with a little bit of pre-processing data along with explainable artificial intelligence. Ramy A. Zeineldin et al. [36] proposed the NeuroXAI framework for analyzing the brain image and developed explanation methods for the visualization map to diagnose and detect the brain tumors in the clinical sectors. Atul Anand et al. [37] proposed a number of deep neural networks using the PTB-XL dataset, which was available publicly, for the recognition of cardiac disorders using ECG signals. Giorgio Leonardi et al. [38] proposed CNN classifiers for the detection of strokes and developed and trace saliency maps used to trace the output of the model to make the model explainable. Zia U. Ahmed et al. [39] developed a stack-ensemble Machine Learning model outline with XAI that can visualize the spatial distribution of lung and bronchus cancer (LBC) and could visualize the relationship between the risk factors for LBC. Michael Merry et al. [40] proposed a new definition of explanation of XAI. Hao Sen Andrew Fang et al. [41] Clinical risk prediction models (CRPMs) uses the characteristic of patients to find the chance of evolving the particular disease but it is failed to had a scope in clinical practice due to lack of transparency. Andreu-Perez et al. [42] proposed multivariate pattern analysis for functional near-infrared spectroscopy (fNIRS) with XAI, which had been developed for the study of the development of the human brain in infants.

5.6. Explainable AI on remote sensing and signal processing

Dongha Kim and Jongsoo Lee [43] proposed a method called the optimal data augmentation method with XAI. A CNN model was developed to detect the quality of vehicle sounds. Optimal data augmentation method developed based on changes obtained for each selected characteristic. Optimal data augmentation method obtained 94.22% of accuracy than the existing method with improvement of 1.55–5.55%. On account of datasets used, the accuracy of standard deviation obtained was 2.13% which is more accurate result. Giorgio Leonardi et al. [44] proposed the XAI method with a classification task of remote sensing using an explanation of the model used a trained DL model with datasets. 10 Explainable AI methods been used in the field of remote sensing along with performance metrics to find the method's performance. Many experiments were done to analyse the overall performance of XAI in different cases (e.g., misclassification, multi-labels and prediction models). Grad-CAM given high-resolution outputs with 0.03 computational time apart from ten XAI methods.

6. METHODOLOGY

6.1 Data Collection

- Identify leading telemedicine platforms utilizing AI.
- Design and deploy surveys for healthcare professionals and patients.
- Extract AI models and decision-making data from the platforms.

6.2 Data Preprocessing

- Clean and structure collected data for analysis.
- Handle missing data, outliers, and inconsistencies.
- Normalize and standardize data where necessary.

6.3 Exploratory Data Analysis (EDA)

- Perform initial analysis to understand the data's characteristics.
- Visualize data distributions, correlations, and patterns.

6.4 AI Model Study

- Analyze and categorize the extracted AI models from telemedicine platforms.
- Understand their decision-making processes and areas of opacity.

6.5 XAI Integration

- Implement explainable AI techniques on the studied models.
- Develop a framework that offers transparency in AI-driven decisions.

6.6 Framework Evaluation

- Test the newly developed XAI framework in controlled scenarios.
- Compare the performance of original AI models against their XAI-enhanced counterparts.

6.7 Validation and Feedback

- Gather feedback from healthcare professionals and patients on the XAI framework.
- Validate the effectiveness of the framework in enhancing trust and understanding.

6.8 Results and Analysis

- Evaluate the overall impact of the XAI framework on telemedicine platforms.
- Analyze improvements in trust, understanding, and system performance.

7. CONCLUSION

The advent of telemedicine, bolstered by the capabilities of artificial intelligence, has undeniably transformed the healthcare landscape, making medical consultations and treatments more accessible than ever before. However, the opaque nature of AI algorithms has raised concerns about the trustworthiness of AI-driven telemedicine recommendations. Our research underscores the pivotal role of Explainable AI (XAI) in bridging this trust gap. By integrating XAI into telemedicine platforms, we can ensure that both patients and healthcare professionals receive transparent and understandable explanations for AI-generated recommendations. This not only fosters trust but also ensures that medical decisions are made with a comprehensive understanding of the AI's rationale. As we move forward, it is imperative for developers, policymakers, and healthcare providers to prioritize the integration of XAI in telemedicine, ensuring that the future of remote healthcare is not only advanced but also trustworthy and transparent.

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