Amalgamation of Transfer Learning and Explainable AI for Internet of Medical Things

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***Abstract*—The Internet of Medical Things (IoMT), a growing field, involves the interconnection of medical devices and data sources. It connects smart devices with data and optimizes patient data with real time insights and personalized solutions. It is mandatory to hold the development of IoMT and join the evolution of healthcare. This integration of Transfer Learning and Explainable AI for IoMT is considered to be an essential advancement in healthcare. By making use of knowledge transfer between medical domains, Transfer Learning enhances diagnostic accuracy while reducing data necessities. This makes IoMT applications more efficient which is considered to be a mandate in today's healthcare. In addition, Explainable AI techniques offer transparency and interpretability to AI driven medical decisions. This can foster trust among healthcare professionals and patients. This integration empowers personalized medicine, supports clinical decision making, and confirms the responsible handling of sensitive patient data. Therefore, this integration promises to revolutionize healthcare by merging the strengths of AI driven insights with the requirement for understandable, trustworthy, and adaptable systems in the IoMT ecosystem.**

***Index Terms*—Wearable sensor devices, Transfer Learning, Explainable AI, Trustworthiness, Data Privacy concerns**

I. Introduction

Traditional healthcare has conventionally relied on in-person visits, paper based record keeping, and limited connectivity between the healthcare providers and the patients.In recent days, we have seen a significant shift towards centralized software applications and databases as the primary means of maintaining medical records. Medical personnel have also faced several challenges, such as limited access to patient information, difficulty performing remote patient monitoring, and a lack of real time insights. These challenges hinder the timely and proactive care for patients. IoMT was introduced to improve healthcare services and ensure timely treatment. It has brought great advances to the medical industry. It leverages interconnected medical equipment, wearables, sensors, implantable devices, and smart pills to enable continuous data collection, remote patient monitoring, and real time analysis. This integration of technology into healthcare facilitates personalized treatments, continuous patient monitoring, and proactive observation of patient health to react instantly to the disease. With IoMT, healthcare providers can get widespread information about the patient, perform effective collaboration, and make data driven decisions which leads to improved patient outcomes and enhanced healthcare delivery.

It is proven that IoMT has huge potential to be used in healthcare. It has revolutionised healthcare by connecting medical devices to generate vast amounts of data related to patient health. The incredible development of IoMT devices has resulted in an exceptional increase in the data generated by these devices. This includes patient health records, sensor readings, imaging data, and other health related information. This huge data explosion presents both opportunities and challenges. On the one hand, the large quantity of data has immense potential for getting more insights, but managing and analyzing this huge volume of information poses challenges. Traditional healthcare organizations are currently facing various challenges in offering effective health services. The vast amount of data generated by IoMT devices poses additional challenges, including the task of effectively storing, processing, and deriving meaningful insights from the diverse data collected. Furthermore, ensuring data security, privacy of patient information, interoperability, and compliance with healthcare regulations adds another layer of complexity. By using the immense data generated by IoMT devices, healthcare providers can unlock new opportunities to provide precision medicine, proactive observations about patient health, and more efficient and patient centric healthcare services.

In the field of machine learning, various learning approaches exist. This includes supervised learning, unsupervised learning, reinforcement learning, and transfer learning. Supervised learning involves training a model using labeled data to make decisions. Unsupervised learning focuses on finding relationships and patterns in unlabeled data. Reinforcement learning creates an agent to make decisions and learn from the feedback from the model based on the rewards and penalties obtained. Transfer learning (TL) enables the transfer of knowledge and learned features from one domain to another, which helps improve efficiency and performance. To deploy any particular learning in any system to make predictions, it is essential to know its strengths and weaknesses. Here are the critical drawbacks of each approach: Supervised learning demands labelled data, and it is sensitive to unbalanced datasets and biases. In IoMT, obtaining quality labelled data is more complex. Lack of supervision and evaluation metrics is the primary drawback of unsupervised learning. As healthcare is a critical and sensitive application, supervision is always required to make decisions about patient health. Reinforcement learning is a trial and error approach that may not be suitable for healthcare applications. Transfer learning also has some limitations, such as domain mismatch and over reliance on the source domain. But it can be mitigated with proper training and the selective transfer of knowledge. Therefore, transfer learning can be the suitable approach to obtain knowledge from a well trained model and fine tuning it to make accurate, reliable decisions in healthcare applications.

AI solutions are essential to the IoMT due to its ability to manage the huge volume of data generated by IoMT devices. This enables real time patient monitoring, offers personalized healthcare, makes predictive analytics for resource allocation, simplifies remote patient care, improves diagnostic accuracy, increases operational efficiency, pushes research advancements, empowers patients, and confirms regulatory compliance. The merging of AI and IoMT promises to transform healthcare by harnessing the potential of data driven understandings while delivering cost effective and patient centric care. However, at the heart of this transformative potential of AI in IoMT lies a critical challenge called explanations of AI decisions, the need for Explainable Artificial Intelligence (XAI). XAI links the gap between the enormous power of AI algorithms and the requirement for transparency and interpretability in healthcare decision making. In this multidimensional territory, XAI helps as the key to unlock the full potential of IoMT, confirming that the insights generated by AI driven systems are not only accurate but also understandable and trustworthy for its stakeholders. This introduction explores into the complicated interplay between IoMT and XAI, exploring how their synergy is ready to reshape the future of healthcare by providing unparalleled new insights, while maintaining vital levels of transparency and accountability.

II. Literature Survey

This section categorizes and analyses the relevant literature in two areas: the impact of transfer learning in healthcare and advancements in XAI for healthcare. Table I depicts the comparison of Deep learning, Machine learning and Transfer learning approaches in the context of IoMT.

The authors in [7] proposed a transfer learning based AI model to detect the patient's sickness based on their facial expressions. They have used a model called the VGGFace Model to identify sick symptoms based on the facial features of a person. This VGGFace model is a new AI model, and acquiring the dataset in the field of healthcare for detecting face is a challenging task. So, authors have used TL to transfer the knowledge obtained from a well trained model. A well trained large dataset model uses lower layers to understand the basic features and upper layers to understand task specific features. So, to transfer knowledge from one model to another, it is enough to transfer only the lower layers. The upper layers can be trained on the new task with a limited dataset available. This transfer learning predominantly suits for scenarios where there is a lack of dataset. XAI is used for giving explanations for the decisions taken by the AI model. Deep learning models are highly complex to understand, and sometimes users are unable to understand how these AI models are making decisions. So, XAI techniques such as Gradient-CAM, XRAI, and LIME were used to provide explanations for the decisions taken. This greatly helps patients and medical practitioners understand and believe in the healthcare system.

The authors in [8] have proposed a transfer learning based XAI approach to detect and interpret COVID-19 infections among patients based on the Chest radiography images. The authors used the VGG-Net model proposed by [9] in both the segmentation and detection parts of the proposed framework. This well trained model consists of nearly 138 million parameters. This is a very popular model trained with images from the ImageNet dataset. It was trained with more than a million images in 1,000 different classes. Additionally, the authors have also used ResNet and the Inception V3 model proposed by [10] and [11] respectively, to enhance the performance of the model. In summary, the authors used VGG16, VGG19, ResNet, and Inception V3 neural network models to obtain the knowledge necessary to enhance and improve the prediction accuracy of the proposed framework. The authors believed that XAI techniques had the potential to contribute to the medical sciences. So, they have also used XAI techniques such as LIME, Grad-CAM, and Deep-SHAP to generate the heatmap, which can help identify the exact infected regions of the patient based on the lung image and justify the prediction made.

III. Preliminaries

The IoMT is a collection of medical devices and applications that can connect to and use healthcare information technology systems and networks. IoMT enables the real time monitoring of patient's vital signs and the communication of data to a cloud computing framework. IoMT can help physicians to monitor, diagnose, and treat patients effectively. The IoMT is changing the face of healthcare by seamlessly integrating medical devices, wearables, and sensors with healthcare systems. With IoMT, patients can receive top notch care from the comfort of their own homes [12]. With the availability of several patient data interfaces to IoMT devices, healthcare providers may now easily make early detects and customise treatment plans. These developments have resulted in better patient outcomes, increased patient participation, and more

TABLE I
COMPARISON OF DEEP LEARNING, MACHINE LEARNING AND TRANSFER LEARNING APPROACHES IN HEALTHCARE

Aspect	Deep Learning	Machine Learning	Transfer Learning
Training Data	Requires large datasets [1]	Typically requires moderate to large datasets [2]	Can leverage pre-existing data and models for transfer [3]
Model Complexity	Complex architectures with many layers [4]	Often simpler models, including decision trees, SVMs [2]	Adapts pre-trained models, reducing complexity [3]
Feature Engineering	Learns features automatically from raw data [4]	Often requires manual feature engineering [2]	Can inherit features from pre-trained models [3]
Task Specificity	Highly task-specific, may need retraining for new tasks [4]	Flexible for various tasks, with manual feature selection [2]	Can be fine-tuned for new tasks with minimal effort [3]
Computational Resources	Demands substantial computing power and memory [5]	More computationally efficient compared to deep learning [2]	Efficient use of computing resources for adaptation [3]
Interpretability	Often considered less interpretable due to complex architectures [5]	Generally more interpretable with simpler models [6]	Interpretable when using explainable transfer methods [3]
Performance	Achieves state-of-the-art results for complex tasks [5]	May perform well but with limitations in certain tasks [6]	Offers a balance between performance and adaptability
Data Requirements	Requires extensive labeled data for training [4]	Less data-intensive but quality of data is crucial [6]	Requires fewer labeled data for fine-tuning [3]
Applications	Image and speech recognition, natural language processing [5]	Predictive modeling, anomaly detection, clustering [6]	Extensive applications in medical image analysis, disease diagnosis, and drug discovery [3]
Training Time	Longer training times due to model complexity [5]	Typically faster training for simpler models [6]	Faster adaptation due to pre-trained models [3]
Adaptability	Less adaptable to new tasks without retraining [5]	More adaptable to a range of tasks with feature selection [6]	Highly adaptable with transfer learning techniques [3]

effective healthcare delivery. The integration and compatibility of multiple technologies and systems present a considerable challenge. Electronic health records, IoMT devices, and health information systems frequently work in isolation, preventing easy data sharing and collaboration. In addition, the digital gap and differences in access to technology may make healthcare inequalities worse, restricting the benefits of technological breakthroughs. To fully utilize technology in healthcare and maintain equitable, patient centred, and effective healthcare systems, it is essential to address these difficulties [13] [14].

A. *Transfer Learning*

Transfer learning enhances the overall training of a new model, and improves the efficiency. When a model needs a lot of resources and time for training, this technique is generally used. Transfer learning is used in many deep learning projects, including neural networks that perform natural language processing or computer vision tasks, as well as sentiment analysis [15]. It is important to note that transfer learning ignores the term ”machine learning” specifically in this scenario [16]. Similar to supervised learning, it is more turned towards a design technique. It refers to a method that addresses issues with idea or multi-task learning, rather than a specific study. The model's ability to forecast events accurately suffers as a result. Transfer learning can be useful at this point because it makes accurate predictions with a lot of data and knowledge [17] [18].

Additionally, transfer learning is essential because it uses the weights extracted from the first model to initialize the weights of the second model when the training data supplied is insufficient [19]. As features are moved from one task to another, transfer learning depends on feature generalization. This implies that datasets are important in this situation. When the dataset used for the second training is similar to the dataset used for the initial training, it has been discovered that transfer learning can produce optimized results [20] [21].

B. *XAI*

XAI is an important aspect of today's AI driven world because of its transparency and accountability in the decision making process of AI models. XAI is used in IoT and AI applications such as security enhancement, IoMT, Industrial IoT (IIoT), and Internet of City Things (IoCT) [22]. In the context of IoMT, XAI can be used for predictive data analytics for healthcare [23]. XAI is a set of processes and methods that allows human users to comprehend and trust the results and output created by machine learning algorithms [24]. XAI describes an AI model, its expected impact, and potential biases and also helps characterize model accuracy, fairness, transparency, and outcomes in AI powered decision making. XAI is crucial for an organization to build trust and confidence when deploying AI models into production [25].

Explainability can help developers ensure that the system is working as expected, it might be necessary to meet specific standards, or it might be important in allowing those affected by a decision to challenge or change that result [26].

XAI uses a variety of techniques and approaches to make AI systems more transparent and understandable. Various approaches of XAI are shown in Fig.1. Ethical considerations and data visualization are also important to make XAI a reality. Linear models are inherently interpretable and are well-suited for XAI due to their simple structure, clear functional meaning, and transparency. Black box techniques such as complex neural networks can provide global and local explanations, leverage visualization, and combine with simpler models to improve accuracy and transparency, even if they are inherently difficult to interpret. Rule-based systems provide interpretability, transparency, and personalization, allowing explicit and understandable decision-making based on sensor data. Surrogate techniques approximate the behavior of complex models and create interpretable models that provide local explanation, reliability, and regulatory compliance. The method of implementation depends on the specific problem and the desired level of interpretability.

C. Motivation of Transfer Learning with XAI in IoMT

Transfer learning is a machine learning technique that involves using knowledge gained from solving one problem to solve a different, but related problem. XAI refers to the ability of AI systems to provide explanations for their decisions and actions [27]. When used together, these technologies can improve patient outcomes by allowing healthcare providers to better understand the reasoning behind a recommendation or decision made by an AI system [28] [29]. IoMT, or the Internet of Medical Things, devices can learn from past experiences and adapt to new situations by using machine learning algorithms to analyze data from a variety of sources, including electronic health records, sensors, and other devices. This can help healthcare providers to make more informed decisions and provide better care to their patients. Combining Transfer Learning and XAI in the IoMT can provide many advantages. By utilizing these technologies, healthcare providers can enhance their diagnostic accuracy, expedite the diagnosis process, and improve patient outcomes [30] [31] . The integration of Transfer Learning and XAI allows healthcare professionals to efficiently analyze patient data, quickly identify patterns, and predict potential health problems before they worsen. Ultimately, the integration of Transfer Learning and XAI in IoMT can help healthcare providers deliver exceptional care to their patients while optimizing efficiency and reducing costs. IoMT refers to the interconnected medical devices that are used to collect and share patient data. With the help of Transfer Learning and XAI, IoMT has the potential to revolutionize healthcare by improving diagnosis accuracy, reducing healthcare costs, and providing personalized treatment [32]. Transfer Learning allows IoMT devices to learn from past experiences and adapt to new situations, while XAI ensures that the device's decision making process is transparent and easily understandable by healthcare providers [33]. Together, these technologies can help doctors make informed decisions and provide better care to their patients.

IV. Technical Perspectives

Integration of TL and XAI to IoMT involves a major technical evolution in the context of handling data in the IoMT scenario. It includes intricate handling right from data acquisition to storage, sharing to security and privacy of data. It also involves a major effort in the process of integration of explainability and interpretability. This section elaborates on the said technical perspectives in this research domain.

A. Data Acquisition for IoMT

Data acquisition relates to the process of acquiring data from various sources. Data is captured, recorded, and stored during the data acquisition process. The data that is collected may be processed and used further, or it may be used in other applications. The information that is recorded may be in the form of numbers, text, audio, images, videos, or sensor data. Data source identification, data collection, data cleaning and processing, data storage, data integration, data validation, and data security and privacy are all steps in the data acquisition process [34].

Technology advancements have made IoMT data collection easier, but it still poses certain challenges. With the rapid increase in IoMT data, obtaining vast amounts of data from various stakeholders such as patients and doctors has become difficult. Different methods and approaches are required to collect structured, unstructured, and semi-structured data. The collected data may contain errors, inconsistencies, or biases that can affect its validity and reliability. It is crucial to protect the privacy and security of the gathered data and comply with relevant rules while adopting a relationship of trust with data sources. Furthermore, data collection systems must be capable of handling data from multiple sources while maintaining interoperability and collecting data in real time [35]. Additionally important are, complying with rules and maintaining a relationship of trust with data sources. Devices for gathering information must be able to handle data from many sources while preserving interoperability. Real time data capture presents new difficulties like latency and data transmission speed. Large scale data acquisition and control can be expensive, especially when dealing with high volume data streams [36].

The IoMT can benefit greatly from the technologies of TL and XAI for data acquisition. TL can handle multiple data sources while maintaining interoperability, while XAI can ensure adherence to rules and maintain trust with data sources like smart objects, health monitoring devices, mobile apps that are integrated with sensors like infrared sensors, medical sensors, smart device sensors, Radio Frequency IDentification (RFID) cameras and Global Positioning System (GPS). XAI can be used to provide transparency and interpretability of IoMT systems.Additionally, these technologies can help overcome challenges associated with real time data capture, such as latency and data transmission speed. TL and XAI offer cost effective solutions for managing high volume data streams, which can be particularly useful for large-scale data acquisition and control that can otherwise be expensive.

B. Data Storage in IoMT

Data storage refers to the organized and structured preservation of data for future use. This process utilizes both physical and digital infrastructure and employs various systems and technologies for secure and efficient storage and management. The type of storage selected depends on factors such as storage capacity, performance needs, cost considerations, and data security requirements. Hard disk drives, solid state drives, and cloud storage are some of the commonly used storage methods [37].

Managing the vast amount of data generated by the IoMT can be a considerable challenge due to the need for maintenance, sorting, and storage. This data is often stored in

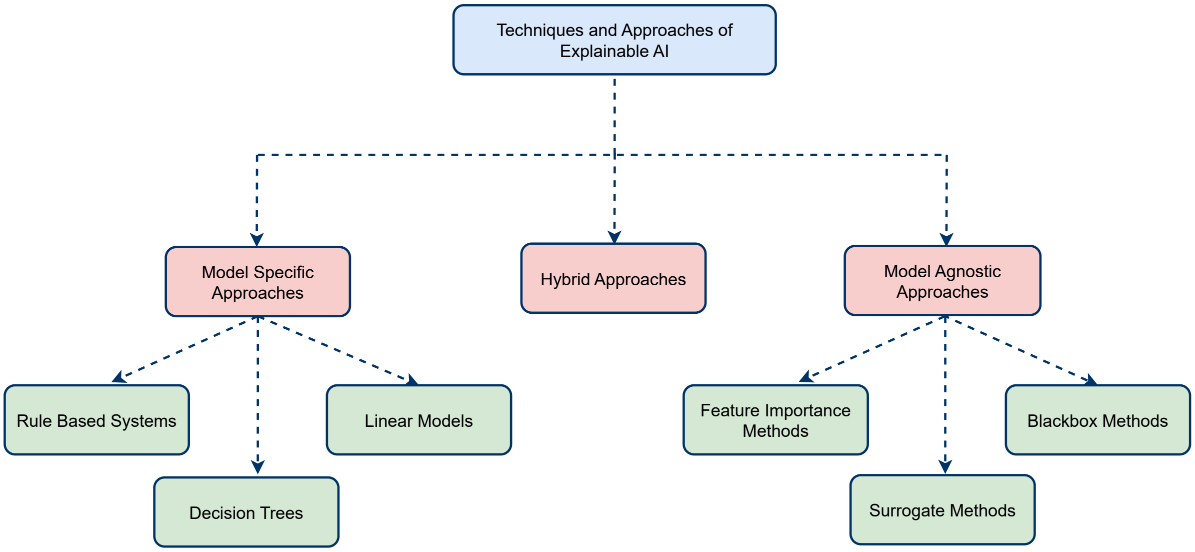

Fig. 1. XAI Approaches

separate silos, and it comes in various forms from different sources, making it difficult to manage [38]. IoMT needs to have a dependable plan for storing data, and it is not feasible to experiment with every trend in data storage. The use of new storage devices may lead to malfunctioning and the possibility of data corruption, which can result in costly data recovery procedures. Furthermore, managing and analysing data is challenging because data is obtained from different sources with no standardization. To guarantee data security, protection measures must be put in place, which can be both time consuming and expensive [39].

In IoMT, patient data can be securely stored with the help of Transfer Learning and XAI. These techniques improve transparency and security measures, guaranteeing the safety of patient data. Transfer Learning applies existing knowledge to new tasks, streamlining the data storage process. On the other hand, XAI offers valuable insights into the AI system's decision making process, building trust and confidence in the system. So, the use of TL and XAI is crucial in safeguarding patient data in IoMT.

C. Sharing of Data from TL to IoMT

The act of data sharing entails granting access to data to individuals, groups, or computer systems. The primary aim of data sharing is to foster collaboration, research, analysis, decision making, and other related endeavours. This practice holds significance both within and across organizations, as well as between various sectors and industries [40]. There are various ways in which data can be shared, including internal, external, and public sharing. Collaborating with different organizations, gaining access to pertinent datasets, lowering costs associated with acquiring data, and promoting transparency and accountability are just a few of the advantages that come with sharing data [41].

When it comes to sharing data in IoMT, privacy and security are of utmost importance. To ensure consistency and seamless interoperability across various healthcare organizations, it is imperative to safeguard sensitive information on stakeholders in a dependable and precise manner [42]. Additionally, legal and ethical considerations may also need to be taken into account while sharing data. Hence, it is crucial to maintain a balance between appropriate access controls and permissions to ensure the sharing of data is both safe and equitable [43].

The combination of TL and XAI is essential for a secure and efficient data transfer from TL to IoMT. TL's utilization of previously learned knowledge improves the accuracy and speed of data transfer, while XAI provides transparency and accountability in the process. This is critical to ensure the safe and effective sharing of sensitive medical data in the IoMT ecosystem. Therefore, the implementation of these two technologies is imperative to achieve a more secure and efficient data transfer in the IoMT.

D. Data Privacy in IoMT

Protecting personal data from unauthorized access, use, disclosure, and manipulation is crucial to ensure data privacy is maintained throughout its development. Various measures must be implemented to safeguard sensitive information and prevent any potential gaps [44].

As IoMT data continues to grow in volume, protecting its privacy becomes increasingly challenging. There is a lack of standardized procedures for managing healthcare data, sharing data is difficult, and data analytics pose potential privacy risks, all of which worsen the issue. Furthermore, data gaps and a lack of user control and awareness contribute to the complexity of privacy issues in emerging technologies, which also require ethical considerations [45].

The IoMT is gaining ground in healthcare, and safeguarding data privacy and security is vital in this field. TL and XAI are two technologies that can play a pivotal role in achieving this goal. TL can enhance data privacy in IoMT by empowering users to comprehend how algorithms function and which data they utilize. This allows patients to make informed decisions about sharing their data while having greater control over their privacy [46]. TL also helps healthcare providers identify any biases in the algorithms they use, enabling them to make more equitable decisions. XAI can also improve data privacy in IoMT by providing transparency into the decision making processes of AI systems. This allows patients and healthcare providers to understand how AI systems are making decisions and which data they are relying on. XAI can also help identify any biases or errors in AI systems, enabling healthcare providers to make more accurate and fair decisions [47]. Generally, TL and XAI are powerful technologies that can bolster data privacy and security in IoMT. By enabling greater transparency and comprehension, these technologies can increase trust in IoMT and guarantee the protection of patient privacy.

E. Data Security for IoMT

Ensuring the security of medical data is of highest importance in transfer learning and explainable XAI for IoMT. It is imperative to safeguard against any unauthorized access, modification, or destruction of this sensitive information. A few techniques for doing this include access control, encryption, and secure communication protocols. It is essential to pay great attention to the data security method when developing machine learning models for IoMT applications.

The IoMT has revolutionized the healthcare industry by enabling the collection of physiological data from patients and providing it to healthcare professionals. However, the propagation of IoMT devices has also led to an increase in vulnerabilities and hacking opportunities. Ensuring data security in IoMT systems is crucial to protect patients and maintain the integrity of healthcare organizations [48]. Some of the key challenges associated with data security in IoMT include security threats, privacy concerns, interoperability, efficient data management, and long-term sustainability. To address these challenges, potential solutions include implementing robust security measures such as encryption, access controls, intrusion detection systems, and regular software updates. Additionally, raising awareness about data security among healthcare professionals and patients is crucial for maintaining a secure IoMT ecosystem [49].

TL and XAI can play significant roles in enhancing data security in the IoMT. TL is an effective approach to transferring knowledge between domains. It allows for the fine tuning of models that have been trained on large datasets, making them suitable for specific tasks within the IoMT [50]. By leveraging pretrained models, TL can help improve the performance and accuracy of security mechanisms, such as anomaly detection and intrusion detection systems. On the other hand, XAI techniques aim to provide transparency and interpretability to AI models, enabling users to understand the decision making process. In the context of IoMT, XAI can help healthcare professionals and patients gain insights into how security measures are applied, identify potential vulnerabilities, and build trust in the system [51]. By combining TL and XAI, IoMT systems can benefit from enhanced security, improved threat detection, and increased user confidence.

V. Applications

The integration of TL and XAI within the IoMT framework is helpful in a variety of applications. This section covers the major IoMT applications that can benefit from the work towards this integration. Fig.2 has shown the integration of TL with XAI.

A. Disease Diagnosis

A key component of healthcare is disease diagnosis, which includes identifying an individual's health condition or determining its genesis and source. It is necessary for developing successful treatment therapies and improving patient outcomes. Typically, diagnosing a disease involves thoroughly assessing numerous variables, such as the patient's medical history, symptoms, physical examinations, laboratory testing, imaging studies, and even genetic or molecular analysis.

When compared to solely relying on human ability, XAI forecast systems minimize detection errors through automatic identification and forecast. According to the results, the RF technique in combination with XAI methods like SMOTE and ADASYN was able to obtain the highest accuracy of 98 percentage. It is noteworthy that the application of XAI approaches has increased the precision and reliability of disease prediction models [52]. In order to forecast heart illness, ensemble classifiers use cardiovascular datasets and the XAI framework. The 303 instances and 14 attributes of the cardiovascular dataset were used in the proposed study. The dataset's associated job is classification, and its attribute features include categories, integers, and real types. SVM, AdaBoost, logistic regression, naive Bayes, KNN, and bagging are used for classification out of which SVM, linear regression and naive bayes showed exemplary performance [53].

While integrating IoMT, several challenges need to be addressed to ensure its effective implementation. IoMT involves the collection, transmission, and storage of sensitive patient data. To avoid unauthorized access, data breaches, or misuse, it is essential to ensure the security and privacy of this data. IoMT involves many devices, platforms, and systems, often developed by different manufacturers and using different communication protocols. A lack of standardized formats, interoperability, and compatibility in various devices and systems may have an impact on data exchange and integration which making it difficult to obtain a complete overview of the patient's health [54].

These issues can be solved by integrating TL and XAI approaches into IoMT illness diagnostics. Models that protect privacy can be created using TL and XAI approaches. Without compromising the privacy of patient data, TL enables models trained on huge datasets to be fine tuned on smaller, local datasets. Furthermore, in IoMT, gathering labeled medical data to train disease diagnosis models is difficult and time consuming. TL solves this problem by allowing pretrained models trained on large, heterogeneous datasets to evolve and translate their learning into the disease diagnosis task at hand. This eliminates the need for large, disease specific datasets, making it data efficient.

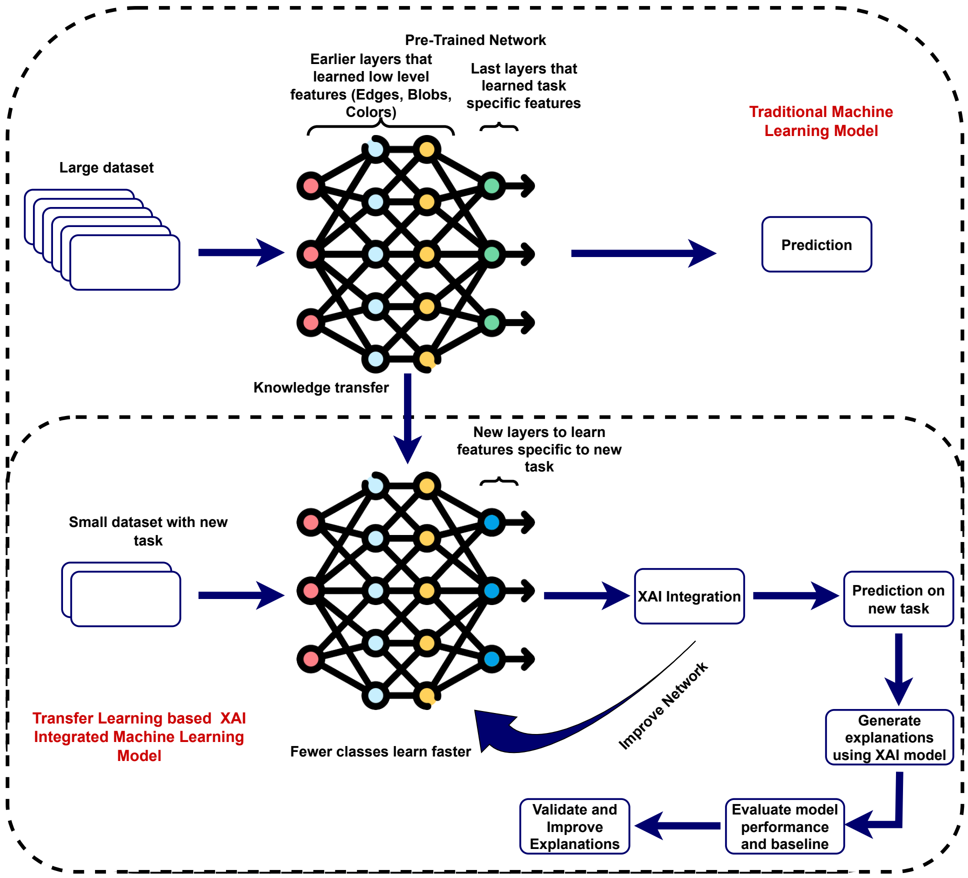

Fig. 2. Transfer learning and XAI Integration

On the other side, with the use of XAI approaches, healthcare providers can analyze model judgments and learn how the model came to a specific diagnosis without disclosing sensitive patient information such as disease and health condition. It can help simplify and standardize data gathered from multiple IoMT devices. TL aids in bridging the gap between various devices and data formats, enabling interoperability and simplifying the integration of various data sources by utilizing pretrained models and transferring knowledge across datasets.

B. Remote Patient Monitoring

Remote Patient Monitoring (RPM) in IoMT involves the use of connected medical devices and technologies to collect and transmit patient data from remote locations to healthcare providers [55] [56]. RPM in IoMT has the potential to revolutionize healthcare delivery by enabling remote monitoring, personalized care, and early intervention. It facilitates early detection of abnormalities or changes in patients' health status. By analyzing trends and patterns in the collected data, healthcare providers can identify potential health risks and intervene promptly. For instance, sudden spikes in blood glucose levels can trigger alerts for diabetic patients, leading to timely interventions or adjustments in treatment plans.

TL and XAI can bring several benefits to RPM in IoMT. TL may be used to modify AI models that were previously trained on massive amounts of data from equivalent patient populations or diseases for new target populations or conditions. It can help in utilizing the knowledge gained from a single device or sensor to benefit the performance of models when applied to data from numerous devices. In order to adapt and advance over time as new patient data becomes available, TL models can be developed for continuous learning. This keeps the monitoring system updated and responsive with respect to varying patient needs.

IoHT based health applications are used by client-side edge nodes to connect with the system using secure wallets. Using the secure keys ensures the privacy of highly sensitive medical data of patients. Blockchain technology is used at the edges which use federated learning model as an efficient solution for performing decentralized computation. This eliminates the need to transfer sensitive data somewhere else. Aggregation of results is done by the global model.various metrics like accuracy, privacy, security and appropriate network characteristics are studied and the proposed method leads to multimodal sustainability [57].

Similarly, XAI offers prediction interpretability, where these methods enable healthcare providers to understand the reasoning behind AI models' predictions in RPM. It can help identify patient data anomalies or irregularities that need immediate attention. Patients are encouraged to actively participate in self monitoring and self management since they can better understand the effects of their physical symptoms or health indicators. XAI helps in the optimization of resource allocation and the identification of cost effective solutions. Healthcare expenses can be decreased by focusing on the most vulnerable patients and offering early interventions which can benefit to both patients and healthcare systems.

C. Personalized Treatment

The use of individualized healthcare interventions and therapies using connected medical devices and systems is referred to as personalized therapy in IoMT. Individualized care is provided by the system through a combination of data collection, analysis, and decision making methods. Healthcare professionals can create treatment strategies that are customized for each patient by taking these considerations into account. This customized strategy improves patient outcomes collectively and enhances the likelihood that the treatment will be successful [58].

TL is important in providing customized treatment in the context of IoMT. With IoMT, broad datasets, and pretrained models are used to extract generic characteristics from a variety of data modalities. This increases the models' ability to evaluate and use patient data for customized treatment by overcoming data shortage and variability. For example, a TL model that has been pretrained on a large dataset of medical pictures can adapt quickly to individual patient X-ray scans. This model can help radiologists by providing patients with more precise and individualized recommendations using the transfer of its understanding regarding disease patterns.

In the field of the Internet of Health Things (IoHT), a multitude of health applications are under scrutiny within the realm of eXplainable Artificial Intelligence (XAI) to measure their effectiveness in terms of privacy, security, and comprehensibility. When considering the implementation of Clinical Decision Assistance Systems (CDAS) powered by AI, a holistic approach is imperative, blending legal, technological, patient-centric, and medical factors. Across various disciplines, an intense focus is placed on the pivotal issues related to the significance of explainability in clinical practice. The technical evaluation of explainability is central, encompassing how it can be achieved and its implications for future progress. Explainability encompasses elements such as informed consent, certification, and licensing of medical equipment [59].

Similarly, XAI is crucial in the personalized treatment, because it enhances transparency, trust, and accountability in AI driven decisions. It allows patients to better understand and participate in their healthcare choices. In the IoMT ecosystem, it also helps to lessen biases, ensure regulatory compliance, optimize treatment plans, and ultimately improve patient safety. As a result, healthcare is more efficient, customized, and morally sound.

D. Medical Image Analysis

Medical Image Analysis is a critical component of IoMT that involves the application of computer algorithms and techniques to analyze and interpret medical images, such as X-rays, CT scans, MRI scans, and ultrasound images [60]. The different stages of the medical image analysis include image segmentation, classification, and detection, image registration, image reconstruction [61].

In the context of medical image analysis for IoMT, TL and XAI can offer substantial advantages. TL makes it possible to transfer information from one area of medical imaging to another, even if the target domain only has only a small portion of labeled data. A model trained on one imaging modality, like MRI, for instance, can be modified and fine tuned to work with another modality, like CT scans, even with less labeled data. Collecting labeled data for training deep learning models in medical image analysis can be extremely difficult and time consuming. TL addresses this issue by allowing models trained on huge, diversified datasets which can be customized on medical images with relatively small sample numbers.

The authors proposed a TL model based on Resnet50 to identify fractures in pelvis bones and GRAD-CAM is used to validate the results. Resnet50 and Googlenet show higher performance upto 97% [62].

Similar to this, XAI approaches can be used to locate and correct biases or flaws in AI models. Healthcare professionals can identify instances when the model may have produced biased or inaccurate predictions by using XAI to explain the decision making process. XAI is an excellent educational resource for medical students, residents, and healthcare workers. It assists people in understanding the complexities of medical image analysis, anatomy, and disease by offering extensive explanations for AI driven image interpretations.

Acute and chronic pulmonary disorders pose a threat to infant and adolescent children. The accurate identification of such respiratory diseases can avoid mortality to a greater extent. Transfer learning based models are employed to efficiently classify COVID-19, Tuberculosis and Pneumonia and differentiate them from normal images using XAI techniques. The result reveals that, in 10 epochs, 79% accuracy is achieved in identifying various disorders [63].

Diagnosis of Paratuberculosis is really challenging and the author used XAI for further clarifying the effectiveness of classification algorithms used. Cahour-Forzy (CHF) scale, and the XAI Explanation Satisfaction scale are used to check the trustability of the system and credibility of the system respectively. Pathologists are trained to work with AI systems and the result of CNN classification model is visualized using gradient-weighted class activation mapping [63].

E. Predictive Maintenance

Predictive Maintenance in IoMT is an emerging field that uses machine learning, advanced analytics, and real time data monitoring to enhance the performance and maintenance of medical devices and other healthcare equipment. It combines these characteristics to optimize maintenance activities and improve the performance of medical devices. By proactively identifying potential failures, predictive maintenance enables healthcare organizations to enhance patient safety, reduce maintenance costs, and optimize equipment utilization, leading to improved operational efficiency and better patient outcomes [64].

TL and XAI are both useful approaches that can be used in the context of Predictive Maintenance in IoMT to boost its efficacy. IoMT often suffers by the lack of available data. TL can help overcome the challenge by utilizing pretrained models from related areas or similar medical equipment. By starting with a pretrained model and optimizing it with the help of the data from the specific IoMT device, TL improves the model generation process. This method minimizes training time and processing demands without compromising performance. Similarly, transparent and easy to understand predictive maintenance models assist in meeting regulatory standards.

On the other side, XAI is critical for predictive maintenance in the IoMT. It guarantees that AI systems' forecasts and suggestions are clearly understood. It enables healthcare companies to more efficiently manage IoMT devices and systems, leading in increased operational dependability and uptime. XAI may assist in resource allocation optimization by offering insights into which components are most essential or likely to fail soon. Furthermore it ensure that resources are allocated where they are most required.

F. Risk Assessment

Risk assessment in the context of IoMT involves identifying and evaluating potential risks associated with the use of connected medical devices, systems, and data [65] [66]. It focuses on evaluating the privacy and confidentiality measures in place to protect this data from unauthorized access, breaches, or misuse.

IoMT relies on network connectivity to transmit data between medical devices, cloud servers, and healthcare providers' systems. Assessing network security involves analyzing the architecture, protocols, and encryption methods used to secure data in transit. In addition to this, IoMT systems must adhere to pertinent laws and standards, including the General Data Protection Regulation (GDPR) [67] and Health Insurance Portability and Accountability Act (HIPAA) [68]. In this situation, risk assessment also considers how well the organization complies with these rules.

The unreliability of AI applications is a significant impediment to the widespread use of modern technology. There are several problems owing to increase in legal and ethical issues for these kind of applications, since clinical and medical judgments affect the well-being of individuals. Additionally, the weak trustworthiness of AI worsens issues with clinical decision-making and undermines accountability for mistakes [69].

In the context of risk assessment in IoMT, TL and XAI are important. They make the risk assessment process in IoMT more comprehensible, transparent, and adaptable. In order to create more accurate risk models for IoMT, TL offers data efficient risk modeling, which enables using knowledge from preexisting risk assessment models or datasets in related fields. Furthermore, it provides robust threat detection which allow information about known threats and attack patterns to be translated to IoMT risk assessment models.

On the other hand, XAI methodologies explain risk scores and projections so that stakeholders understand how risks are determined and quantified. It offers the identification of vulnerabilities, which includes finding the IoMT system's most influential features or elements. Furthermore, it helps in ensuring the required regularity compliance. IoMT risk assessment need to keep up with the latest risks and technological advancements. In this aspect, XAI systems may examine previous risk assessments to offer changes which allow healthcare organizations to constantly update their risk assessment models.

VI. Challenges and Future Directions

The capabilities of TL and XAI in the IoMT have been discussed thus far. IoMT has the potential to revolutionize healthcare by connecting medical devices and applications and enabling the gathering, analysis, and sharing of healthcare data. To properly use these technologies in the healthcare sector, a number of issues must be resolved. Fig.3 highlights the major open challenges that might be faced while integrating TL and XAI in real life IoMT applications

Leveraging TL and XAI techniques in IoMT applications offers immense potential for improving healthcare outcomes. However, several challenges must be overcome. Addressing the scarcity of labeled data, adapting models to the medical domain, ensuring interpretability, enhancing security and privacy measures, and addressing ethical considerations are crucial for successful implementation of TL and XAI in IoMT. This work represents a list of challenges that can be faced in the integration of TL and XAI to IoMT setup. Collaboration among researchers, healthcare professionals, and policymakers is essential to tackle these challenges and harness the full potential of TL and XAI in the IoMT landscape.

A. Open Challenges

1) Data in IoMT: In the realm of healthcare, where data is exceptionally sensitive, it is crucial to incorporate strong security and privacy measures to instill trust among stakeholders. This will in turn aid in mitigating another challenge of data acquisition. Data acquisition challenge can be easily overcome by showcasing the security robustness and privacy preservation in the system. The acquired data comes along with another challenge of expert labeling. There is a scarcity of labelled data which also hinders the supervised learning techniques to be integrated, leaving TL and XAI integration even more tricky. The health data often exhibits an imbalance, primarily because there is more data available for common diseases than for rare ones. Such data imbalances can lead to biased AI models. Assuming data is available and accessible from the IoMT system at hand, the data may originate from diverse sources such as sensors, clinical systems, wearable devices, and mobile health applications. Standardizing this data poses a challenge, especially when dealing with live streaming data and the need for real time services. Also it is essential to ensure the protection of sensitive medical data while making it available for interpretability.

2) Transfer of knowledge: Medical data collected from different sources or locations may also exhibit domain shifts, where the underlying data distributions differ. TL across such domains can be challenging, as models may fail to generalize

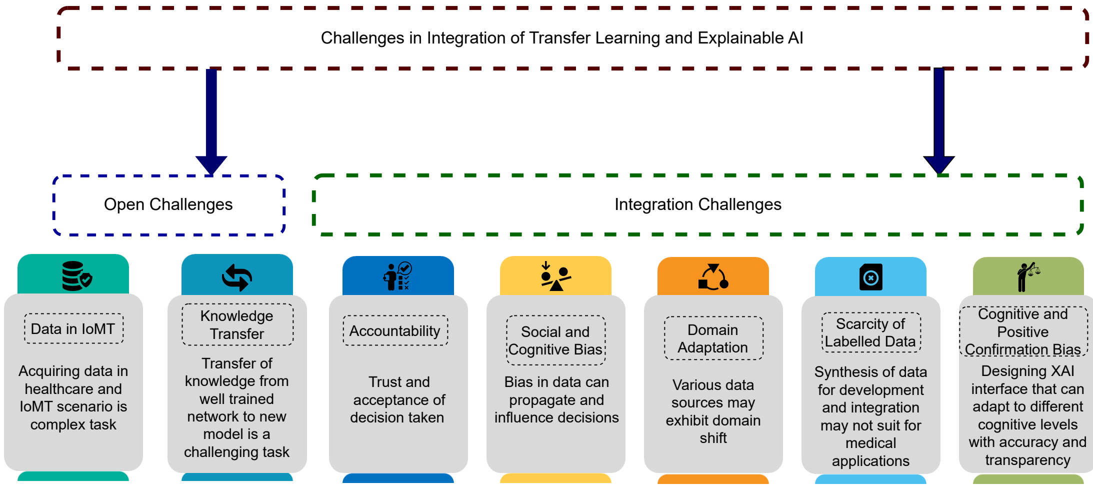

Fig. 3. Challenges in Integrating TL and XAI in IoMT

effectively. Thus, data heterogeneity becomes a challenge for knowledge transfer.

3) XAI: While adding XAI, the major challenge faced in the IoMT domain will be ensuring data privacy and security while providing transparent AI driven insights requires sophisticated encryption and access control mechanisms. The nature of IoMT domain is real time. Incorporating explainability in real time with high predictive accuracy is a challenge that is difficult to mitigate.

B. Integration Challenges

1) Challenges while integrating TL to XAI frameworke: Considering the open challenges, XAI is data and energy intensive [70] posing a continuous requirement of computing system and IoMT devices streaming real time data. Also human level accuracy can only be achieved by appropriate hyper parameter optimization and tuning. While integrating TL to XAI the open challenges, the open challenges outlined in the preceding section concerning data will resurface, presenting potential integration risks and complications. Challenges that may be considered to be mitigated while integrating TL and XAI are summarised below:

- Domain Adaptability: This challenge manifests in multiple instances at different junctures in context of IoMT, inviting the possibility to incorporate partial TL or multi source TL. This in turn requires human machine interaction to be incorporated for feedback system to enhance explainability. In the secure setup of IoMT, such feedback system will add to the complexity of securing the system further.
- XAI Framework: Achieving a comprehensive XAI framework is inherently challenging, encompassing hurdles related to formalizing explanations, quantifying them, and ensuring overall comprehensibility. Generic framework development is essential to handle multiple categories of IoMT applications.
- Explanation maps in XAI: To achieve enhanced interoperability and verify accuracy, the challenge lies in enhancing the visualization of XAI explanation maps. Despite the advancements in technology, such as the introduction of solutions like SHAP and LIME, achieving a visualization equivalent to human level comprehension in understanding explanations remains a challenge yet difficult to overcome.

2) Challenges while integrating TL and XAI to IoMT: While integrating TL and XAI to IoMT the major challenges will be:

- Scarcity of labelled data: Mitigating the requirement of sufficient labelled data will require domain expert's involvement to a great extent. The correctness, generalization and efficiency of the model will be highly dependent on domain experts. These experts are not easily available and thus the scarcity of labelled data is the most difficult to handle. This synthesising of data for development and integration does not suit the medical applications.
- Domain adaptation: Medical data collected from various sources will exhibit domain shift and induce a challenge in integration of TL and XAI to converge towards an efficient generalized model.
- Cognitive level vs positive confirmation bias: Designing XAI interfaces that can adapt to different cognitive levels while maintaining accuracy and transparency poses a significant integration challenge. Moreover, medical professionals may have prior experiences or beliefs about specific treatments, and these biases can influence their acceptance of AI driven recommendations, even when the explanations provide evidence in the contrary.
- Social and cognitive bias: Data bias can permeate through XAI, and XAI systems have the potential to exacerbate these biases within the domain of medical decision making. XAI systems, when trained on biased data, may perpetuate health disparities. In the context of ethical medical decisions, social bias must not propagate through XAI integration to IoMT. One solution is having diverse data to avoid social bias but labelled data is already scarce.
- Accountability: Trust and acceptance of such systems in the medical domain depend significantly on the clear

definition of accountability, determining who will be held responsible and accountable if the designed model suggests wrong solution? With TL and XAI, models trained on existing data and adapted for specific medical tasks, make it challenging to attribute responsibility to a particular individual or entity. Also with the advent of deep learning, TL integration may turn out to be a black box where internal decision making will be difficult to be justify, which may not be tolerable in case of medical applications. Moreover, combination of TL and XAI will create more complex models resulting in a debating situation around who will be accountable.

In summary, addressing these challenges requires a multidisciplinary approach, involving AI researchers, medical professionals, ethicists, and policymakers. Integration of TL techniques can further enhance the robustness and efficacy of XAI systems in IoMT. By promoting fairness, transparency, and user centric design, XAI can be integrated responsibly in IoMT, improving patient care while minimizing the impact of social and cognitive biases.

Future research can be conducted using two distinct approaches:

Parallel Approach: Aligning explainability elements closely with users' decision making processes, such as presenting influential training data samples. *Orthogonal Approach*: Focusing on AI decision making aspects less relatable to humans to address potential issues and establish realistic user expectations. [71]

VII. Conclusion

In conclusion, the amalgamation of TL with XAI in IoMT is a radical development towards revolutionizing healthcare. This synergistic integration not only enhances diagnostic accuracy and data efficiency but also endorses transparency and trust in AI-driven medical decisions. As IoMT continues to evolve, the fusion empowers personalized medicine, supports clinical decision-making, and guarantees responsible data handling. However, it is vital to address challenges related to privacy, regulation, and continuous model adaptation to unravel the full potential of this integration. As a conclusive recommendation of this integration, it is establish a clear ethical framework to guide decision-making and uphold principles of data privacy, fairness, and accountability. The IoMT devices have to be continuously monitored and improve these systems to adapt to evolving medical knowledge and patient needs while collaborating across disciplines, involving AI experts, medical practitioners, data scientists, and ethicists. It is also essential to ensure rigorous regulatory compliance to build trust among stakeholders and prioritize the design of patient-centered IoMT solutions, fostering acceptance and adoption while ultimately improving healthcare outcomes. Ultimately, this transformative combination promises a brighter and more insightful future for effective healthcare delivery and decision-making processes in the IoMT era.

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