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RESEARCH ARTICLE

Secure IoMT for Disease Prediction Empowered With Transfer Learning in Healthcare 5.0, the Concept and Case Study

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ABSTRACT Identifying human diseases remains a difficult process, even in the age of advanced information technology and the smart healthcare industry 5.0. In the smart healthcare industry 5.0, precise prediction of human diseases, particularly lethal cancer diseases, is critical for human well-being. The global Internet of Medical Things sector has advanced at a breakneck pace in recent years, from small wristwatches to large aircraft. The critical aspects of the Internet of Medical Things include security and privacy, owing to the massive scale and deployment of the Internet of Medical Things networks. Transfer learning with a secure IoMT-based approach is considered. The Google net deep machine-learning model is used for accurate disease prediction in the smart healthcare industry 5.0. We can easily and reliably anticipate the lethal cancer disease in the human body by using the secure IoMT-based transfer learning approach. Furthermore, the results of the proposed secure IoMT-based Transfer learning techniques are used to validate the best cancer disease prediction in the smart healthcare industry 5.0. The proposed secure IoMT-based transfer learning methodology reached 98.8%, better than the state-of-the-art methodologies used previously for cancer disease prediction in the smart healthcare industry 5.0.

INDEX TERMS IoMT, transfer learning, deep machine learning, histopathology, image processing, lung cancer.

I. INTRODUCTION

Cancer is the second leading cause of death in the world. In 2020, more than 19.2 million new cancer cases will be reported worldwide, with 9.95 million deaths [1]. There are thousands of living cells, and when the body needs more cells, the existing cells split and proliferate. There is a natural process of cell death and replacement when cells reach a specific age or amount of damage. In the absence of this checkpoint, the injured cells would proliferate and ultimately form a tumor. Pulmonary and colon cancer account for a disproportionate share of cancer deaths in both sexes. Cancers of

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the lung and colon are expected to cause 4.14 million new diagnoses and 2.75 million fatalities globally in 2020 [2]. A smart healthcare system is usually Internet-connected, allowing you to control a wide range of smart devices, each of which plays an important role in your and your family's health [1]. The Internet of Medical Things (IoMT) is the underlying technology that connects smartphones, laptops, and wearables to form a network of intelligent healthcare devices [2]. Solutions for more accessible and secure intelligent healthcare systems can make citizens' lives easier and safer. It includes important features like habit tracking and safety tests, compelling customers and system developers to conduct extensive research [3]. Important concerns, nevertheless, including privacy protection, confidentiality, and usability, need to be resolved. When it comes to engaging with crucial concerns like privacy protection, data protection, and information-privileged access, federated learning (FL) is the way to go. Every local model sends its model weights to the central system, which is then used to build the primary model. Federated learning [4] is presented for overcoming privacy issues. The permutation [5] of a small dataset of patients in various hospitals creates a well-trained model that meets the overall goal of better evaluation and categorization. In FL, resource efficiency management [6] is also considered.

The concept of the Internet of Medical Things (IoMT) enhanced with federated learning with was initially considered by various studies, e.g., [7], [8], [9], in addition, several researchers had also studied the concept and new applications emerged, e.g., [7], [9], [10], [11], [12], [13], [14], [15]. In this study, we consider cancer prediction within the general concept of a secure IoMT. An IoMT-based intelligent prediction [16] system is presented for breast cancer empowered with deep learning. A smart healthcare system [17] for multidisciplinary diabetic disease prediction is presented. Data fusion and deep ensemble learning were adopted for prediction. The IoMT-based smart monitoring [18] system was presented to diagnose COVID-19. The lightweight encryption technique [19] is used for IoMT applications to enhance the security of the medical image. Evolution of industry and blockchain era [20], monitoring price hike and corruption in smart govt and industry 4.0. A novel re-source-oriented Distributed Mobility Anchoring (DMA) framework [21] for IoMT devices in 5G networks is presented.

Model training is difficult due to the variability of data, device capabilities, and patient participation availability. Edge computing [22] collects data at each node in smart healthcare hospitals, while fog computing [23] is employed to connect and transmit data across these nodes. This strategy may be difficult to implement because no single source contains all medical/health information. This information is available to consumers from any location, saving them time and effort. Interoperability and different data standards or formats are significant obstacles when merging data. Many people have worked for years to create a system that keeps all medical data centralized or decentralized and accessible from any location. However, due to security concerns, they have been unable to implement it. Additionally, multiple cloud-based data storage sites are possible, which could result in duplicate records, confusion, and delays. These unnecessary and costly tests go unutilized, putting the patient at risk. Another thing to be aware of is prescription fraud. Unauthorized individuals cannot access other data from this vantage point. Many businesses have spent the last few years focusing on data security, ensuring that the data stored in their systems are protected from unauthorized access. As a result, healthcare providers are looking for more secure ways to store dispersed personal health information on a system or network.

Because of the variety of available sources, transfer learning in the health sector is particularly fascinating. For example, in the case of customized therapy, we may transmit knowledge between multiple hospitals or electronic medical records, among datasets with varying experimental conditions, and even between individuals. Furthermore, this situation allows for the extraction of knowledge from multiple sources, a process known as multi-source transfer learning [24]. In cases involving sparsely labeled training data, transfer learning techniques can result in considerable increases in classification performance compared to standard models employing well-specified statistical features or task-specific deep models. Moreover, utilizing pre-trained models provides little tuning effort and, consequently, rapid adaption [25], [26]. Transfer learning is used in this study to compare the accuracy of the produced model to the accuracy of the pre-trained model.

To circumvent this, we will apply transfer learning [27], another topic of intense research in computer vision. We employ transfer learning, which employs a previously trained model, to learn from a dataset. It saves us a lot of time in training and handles several important tasks at the same time. We will be able to fine-tune our networks over time for greater precision and simplicity.

Edge computing is the technique of locating data processing resources physically closer to the device or sensor that generated the data. The term "edge computing" refers to the practice of moving computation closer to the network's or device's periphery, which improves processing speed, bandwidth, and control over user data. By doing computations at the network's periphery, or "edge," edge computing lessens the need for massive amounts of data to be sent between central servers, the cloud, and endpoint devices or other edge locations. This is especially the case in cutting-edge fields like data science and cognitive technologies. The use of information sources and equipment that are geographically closest to each other is what makes "edge computing" so efficient [28]. This, in theory, improves the performance and efficiency of the application and device. The Man in the Middle attack [29] is proposed. The major contribution of this research was to secure the patient data received through IoMT devices. Brain tumor classification [30] via IoMT-enabled

Computer-Aided Diagnosis (CAD). This paper applies the Google-net features technique and advanced machine learning algorithms to classify brain tumors better. A new adaptive cognitive sensor Node is proposed for electrocardiogram (ECG) Monitoring via IoMT. Convolutional Neural Network (CNN) was trained to classify the ECG waveform in this research.

The proposed IoT framework for heart disease prediction in a cloud environment based on an MDCNN classifier and MSSO-ANFIS [31], [32] can enable continuous monitoring of patient's vital signs, early detection of heart disease, and timely intervention, thereby improving patient outcomes and reducing healthcare costs is studied.

The "Secure framework for authentication and encryption using ECC via IoT-Based Medical Sensor Data [33]" is a proposed system for securing the transmission of medical sensor data in the context of the Internet of Things (IoT). The authors suggest that their proposed framework can help to mitigate security risks associated with the transmission of sensitive medical data, such as the unauthorized access, modification, or interception of the data. By ensuring the confidentiality, integrity, and authenticity of the data, the proposed framework can help to maintain the privacy and safety of patients and medical professionals involved in remote monitoring and treatment.

CNNs (convolutional neural networks) are commonly used to classify images in the field of artificial intelligence. Before submitting the input to the neural network, data convolution, maximum pooling, and flattening are all performed. Several inputs are used to configure the weights for it to function. The weights can be calculated and evaluated after the information has been processed through the obfuscated levels. After receiving input from the cost function, the network enters a back-propagation stage. The process is repeated until the weight of the input layer is in the best possible position, at which point the program terminates. An epoch represents how many times this pattern has been repeated. Unfortunately, training a neural network model takes a long time. Transfer learning, another active area of research in computer vision, will assist us in overcoming this challenge. To learn from a dataset, we use transfer learning, which employs a pre-trained model. The amount of time we save in training and the number of tasks it completes at the same time are both significant. We can fine-tune our networks to make them more efficient and user-friendly with more data.

Transfer learning is a technique in which a model developed for one problem is used to solve another. Transfer learning is a deep learning technique that involves training a neural network model on a problem similar to the one being solved. The learned model's layers are then used to train a new model on the problem of interest. Transfer learning accelerates neural network model training while decreasing generalization error. Weights from previously used layers can be used to start the training process and then switched to the new challenge as needed. Transfer learning is viewed as a type of weight initialization approach in this context. This might work if the first related problem has more tagged data than the problem of interest and the problem structure is the same in both cases.

In this work, AlexNet, a model that has been developed for the categorization of cancer pictures, was used. This network has about 60 million constraints and comprises 65,000 neurons. AlexNet has trained on over a million images from over a thousand classes in the ImageNet database. The network's architecture consists of five convolutional layers and three fully linked layers [34]. In a smart healthcare system, multiple machine-learning algorithms can improve disease prediction. CNN excels at image datasets of human disease, but Artificial Neural Networks (ANN) and their derivatives excel at numerical datasets. The Internet of Things collects data from sensors because they are useful tools for analyzing automated e-healthcare systems and customers. This category contains three types of devices: sensors, interaction, and smart healthcare. Sensors collect data, which computers then process. The heart can be monitored through the sensor with the help of the smart healthcare system, for example, by managing the heartbeat level. Wearables, closed-circuit devices, and other objects comprise the IoMT network system's edge layer. Capturing and storing data allows information to be acquired and processed from these edge and fog nodes. The main benefit of our proposed methodology is that the patient's data is not sent to an insecure platform.

Compared to previous techniques, a "secure IoMT-based disease prediction system via transfer learning" offers several advantages for the healthcare industry. Firstly, it utilizes IoMT devices, which provide real-time and continuous monitoring of patient health, leading to more accurate and timely disease prediction. Secondly, transfer learning enhances the accuracy of disease prediction models by utilizing pre-trained models and data from different sources, reducing the need for large amounts of patient data for training. Thirdly, the system ensures data security and privacy through the use of encryption and secure communication protocols, addressing concerns regarding the confidentiality of patient information. Overall, the proposed system is a promising solution for the healthcare industry, providing better patient outcomes and reduced healthcare costs.

The main contribution of this research is as follows:

- The key objective of this research is to ensure the privacy & security of 'patients' data and the secure automated e-healthcare system.
- To improve the forecasting effectiveness of the model, we have implemented transfer learning and data augmentation strategies to strengthen the training process and ensure that model training is carried out effectively.
- The performance of the suggested model has been examined using a variety of performance assessment indicators.

- The proposed IoMT-based transfer learning model provides a better solution for accurate disease identification and treatment.
- The proposed TL model is entangled with IoMT devices or sensors for faster and more secure data transmission.

The following is a breakdown of the paper's structure: Section II highlights the most recent advances in lung disease detection and monitoring reported in the literature. The research methods, feature extraction, feature selection, and proposed TL model are all covered in Section III; the dataset selection, preprocessing, and results & discussion are presented in Section IV; the conclusion and future work are discussed in Section V. References in Section 6.

II. LITERATURE REVIEW

A recent study found that cloud-based medical records have several drawbacks, the majority of which relate to the collection and evaluation of medical or healthcare-related data from various databases that are accessible from anywhere. Furthermore, no infrastructure exists that securely stores and makes all medical or healthcare-related data, such as lab tests, imaging, or a patient's prescriptions, accessible from anywhere in a cloud-like environment. Many medical-related departments now store data using computer systems and software rather than a manual system, reducing the amount of human labor as well as the time and effort required to manually collect data. Users cannot obtain data online from the comfort of their own homes; instead, they must travel to the location, which takes time. The tasks and responsibilities associated with smart homes are expanding as a result of recent developments in Information and Communication Technology (ICT) and the Internet of Things (IoTs). Smart bins, for example, eliminate the need for people to transport trash cans to the dump manually [35].

Real-time data collection and transmission constitute a smart healthcare system. Smart technology could provide automated services and data from a variety of medical devices, such as a smartwatch, blood pressure monitor, and electrocardiograph. Without user intervention, systems employing these new technologies are integrated into the community's computer-based interactive health system [36]. Depending on their settings and the configuration of the smart healthcare network, consumers may be able to control how they utilize various medical devices to track and manage their health to optimize the design of health products. The Internet of Things and intelligent living is gaining importance in healthcare. As we explained in our previous post, the smart healthcare network is comprised of numerous embedded computers connected to the internet and linked to various IoMT devices. In recent years, wireless networking services have replaced wired networking services [37]. Thanks to a recent breakthrough [38], it is now possible to manage appliances across gates, both inside and outside the building. Smart healthcare systems are predicted to become more effective and systematic with the introduction of 5G, a fifth-generation mobile networking technology, the integration of several industries, and the rise of hardware. Data has become a primary source of intelligence in recent decades, and smart solutions for real-world issues, including Wireless Networking, Bioinformatics, Agriculture, and Finance [39] have opened up new possibilities. These solutions are data-driven and include user-friendly information to help users do jobs more quickly. This produces knowledge, customizes consumer perceptions, improves customer interactions, increases operational efficiency, and mandates the usage of emerging technology. Several complex and modern innovations have been developed to make people's life easier [40]. Large amounts of data are saved in such systems, and archiving this constantly changing mate-rial presents security concerns. Several sophisticated and technological technologies make people's lives easier [36] for smart cities presented in this paper.

The Precision-weighted FL [37] method to classify images in the MNIST dataset was considered. The author discusses attack detection [41] in the medical and physical systems using FL. E-healthcare monitoring systems that are automated have been proposed. All communication was done through network devices connected to link nodes for better patient treatment. There was the prospect of a cyber-attack via these devices due to the heterogeneity of devices linked to automated systems. An intrusion detection system was proposed for an attack in Florida via the IoT [42]. A multivariate dataset was used in this study. The author presented an FL-based [43] pedagogical analysis in the education sphere through a learning-based incentive mechanism. The author of this work offered an FL server that could be run locally without affecting the properties or data of the existing system. The failure to consider model efficiency was a fundamental flaw in this study. This research proposes an FL framework based on deep knowledge tracing [44]. Data security has been thoughtfully considered in this paper. However, one important flaw in this article is that the confidentiality of pupils was not taken into account. FL of predictive models in Electronic Health Records (EHR) developed a decentralized optimization framework for hospitalization prediction [45]. The author contributes to the decrease of communication costs and convergence rate in this study. The absence of a simulation result retrieved via FL was a major flaw in this paper. his research proposed dynamic fusion-based FL for COVID-19 detection [46]. Using a fusion-based FL method, image data was used to diagnose COVID-19 patients. The evaluation parameters provide good results in this article. The privacy of patients' data was overlooked as a fundamental flaw in this planned medical picture analysis. A personalized FL [34] for IoT applications was presented based on the cloud-edge framework [47]. The cloud-edge architecture for the personalized FL framework was introduced in this publication.

The proposed architecture is a viable option for enhancing development, ensuring high precision, and decreasing communication costs. The primary flaw of this proposed cloud-based edge-based architectural framework was that it did not

TABLE 1. Limitation of previous work.

Studies	Contribution of their works	Limitation of Works
Khan et al. [49]	To overcome the attack of Man in the Middle in IoMT. The major contribution of this research was to secure the patient's data received through IoMT devices by sending smaller signatures derived from authentication codes.	The patient's data is being shared via IoMT devices. There is a chance of data corruption and privacy leakages in this way. Cyber-attack can also harm the whole healthcare system.
Abbas et al. [13]	Proposed an automated smart healthcare system that directly transmits patient data in real-time.	The major drawback of this study was patient data privacy & authenticity.
Abbas et al. [38]	Several complex and modern innovations have been developed to make people's life easier by the automated system was considered in this study	To control the huge amount of data properly. Data privacy & security are concerns.
Thamilarasu et al. [43]	Attack detection in the medical and physical system using Federated learning.	All the communication is made through network devices (node to node). Cyber security issues.
Nguyen et al. [44]	An intrusion detection system was proposed for an attack in Florida via the IoT.	The data is received through IoT-based devices. Privacy & security were not considered in this study.
Brisimi et al. [42]	The author contributes to the decrease of communication costs and convergence rate in this study	The absence of a simulation result retrieved via FL was a major flaw in this paper.
Zhang et al. [48]	Used a fusion-based FL method, image data was used to diagnose COVID-19 patients in this work.	The evaluation parameters provide good results in this article. The privacy of patients' data was overlooked as a fundamental flaw in this planned medical image analysis.
Mehmood et al. [50]	Proposed an automated system that improved lung disease identification accuracy, transfer learning, and class-selective image processing techniques.	A major drawback of this study was patient data privacy & authenticity.

take model efficiency into account. This work suggested an FL strategy for preserving privacy [48] in traffic flow. In this study, the FL algorithm was developed to predict traffic flow. In this approach, a viable solution to reduce communication cost overhead was provided. The absence of numerical simulations for privacy is the paper's primary deficiency. The Fed-GRU algorithm was used to simulate and evaluate the results in this paper. The privacy of misbehavior detection [49] through the Internet of automobiles utilizing FL is preserved. The FL method was used in this paper to protect privacy in automotive networks. The proposed model demonstrated satisfactory accuracy and other evaluation characteristics in this paper. The weights of FL models were not protected, which was a key issue in this paper. The FL technique for traffic collision avoidance [50] was proposed in this study. Using this method, transfer reinforcement learning agents' knowledge can be supplied in trial time. The importance of FL simulation latency for the overall performance of the proposed model was not explored in this research. Deep and Federated learning approaches have been used to conduct a comprehensive study on brain tumor diagnosis. This study provides a comprehensive analysis of all aspects of brain tumor research, including methodologies, datasets, and classifiers. This work presents deep learning-based brain tumor analysis [51]. The main contribution of this research study is a comprehensive analysis of brain tumors, their history, and the future issues that will be confronted in diagnosing and predicting brain tumors in humans. This work discusses feature selection and segmentation [44] in MRI images for brain tumor diagnosis. This publication discusses lung cancer disease detection [52]. Transfer learning and class-selective image processing techniques improve lung disease identification accuracy. The major limitation of previous studies is shown in Table 1.

Finally, simulation findings showed that transfer learning for lung disease categorization in an e-health care monitoring system proved to be more accurate with patient data privacy.

III. PROPOSED IOMT-ENABLED INTELLIGENT SYSTEM FOR LUNG DISEASE PREDICTION

This paper discusses the proposed IoMT-enabled Intelligent System for lung disease prediction in the healthcare industry 5.0 with transfer learning. The proposed model is depicted in Figure 1. The phases of the proposed IoMT-enabled Intelligent System with a TL model for predicting lung cancer in patients using a smart healthcare system are as follows:

The proposed model's flowchart, as shown in Figure 1, is divided into several phases, including (1) data collection through IoMT devices, (2) raw data preprocessing, (3) data distribution for training and validation in proposed

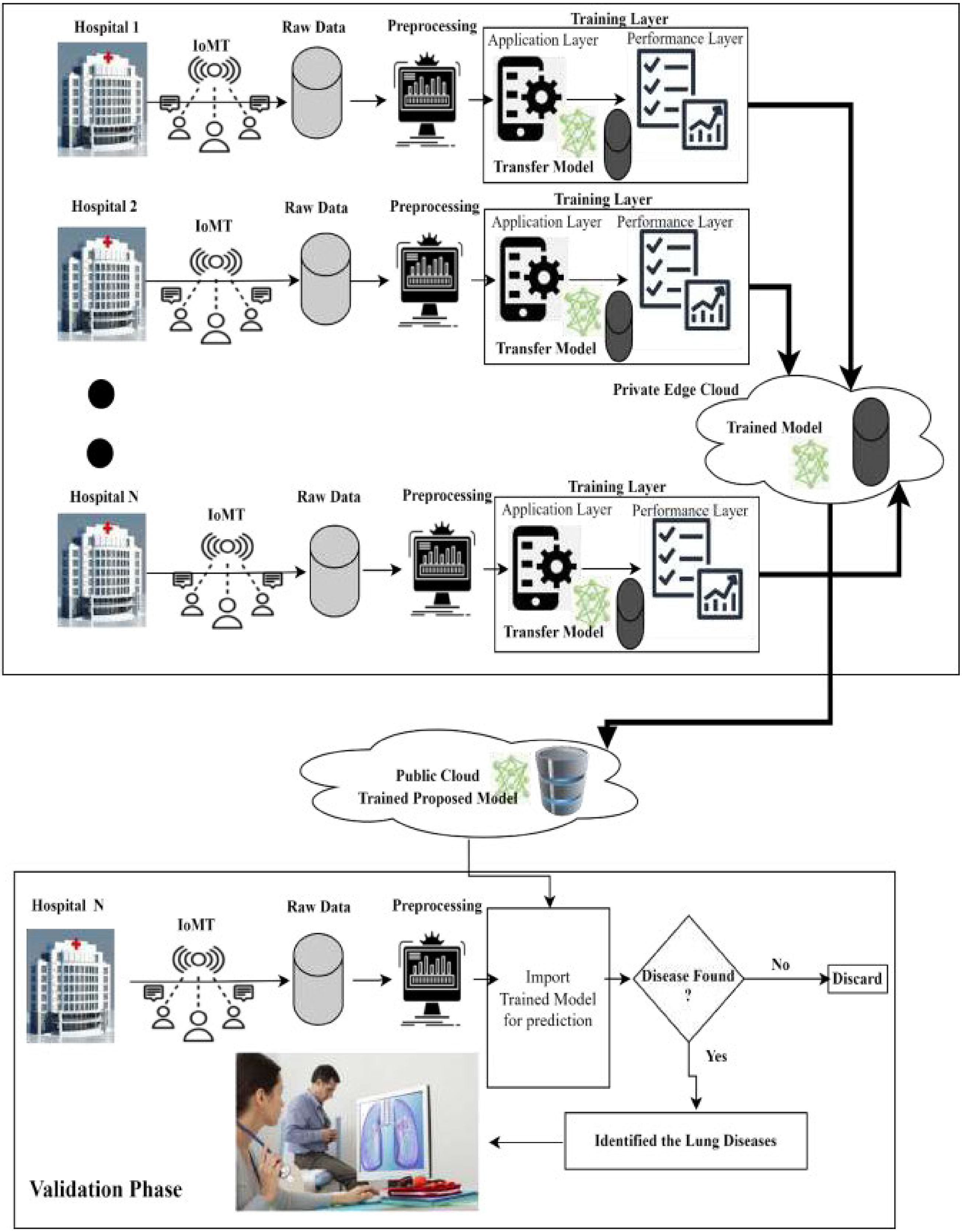

FIGURE 1. Proposed transfer learning model.

IOMT-based Transfer learning model, (4) Private edge cloud Layer of storing the proposed trained model (5) public cloud layer, and (6) validation layer. For privacy reasons, data on patients is collected individually from hospital A to hospital N. Using the IoMT, all of the data collected from these facilities is transferred to a raw database. During transmission, the data obtained from patients via wireless connection become noisy, necessitating certain preprocessing steps to remove the noise for improved interpretation. Each hospital's preprocessing layer handles all patient data to handle missing values and normalize data for subsequent processing. There are two elements to the training layer: (1) the application layer and (2) the performance layer. A TL model is used in the application layer to classify diseases based on the processed patient data. The outputs of the TL model are delivered to the performance layer after the application layer to check the required accuracy standards. If the model's performance fails to meet the specified requirements, retraining the TL model on the given dataset. This process is repeated until all of the required requirements are met. The TL model is finally transferred to the private edge cloud for further optimization after the model reaches the required threshold, as shown in Figure 1 of the proposed TL model for lung disease prediction in smart health care. 5.0.

Figure 1 shows that the TL model, which is currently stored in a private edge cloud is transferred to a public cloud for validation purposes. The hospitals are labeled with names such as Hospital A, which contains the data of all the patients in the area, as well as Hospital 2, Hospital 3, and Hospital N. In Figure 1, a Trained TL model is maintained in private edge clouds for predicting lung illness using Google Net models in a heterogeneous context. After completing all the proposed TL model steps, the planned generalized trained TL model is ready for lung disease prediction in smart health care 5.0.

The pseudo-code of the proposed model is shown in Figure 2 for more clarification and understanding. The pseudo-code flow chart is working as under; at the initial stage, image data collection is done through IOMT devices from different hospitals. Nowadays, different latest tools are being used for image capturing in hospitals. These devices are in real-time linked with IOMT for data transferring to storage devices like edge nodes or cloud-based servers for further processing.

A. DATASET

We used the LC25000 [53] dataset, containing 25000 pictures of cancer tissue in the lungs and colon.

Lung tissue images are divided into five (05) categories: adenocarcinoma, squamous cell carcinoma, and benign, whereas colon tissue pictures are divided into two groups: adenocarcinoma and benign.

After receiving the images dataset, these images need to be preprocessed for noise removals. After preprocessing, the image dataset is divided for training and validation in machine learning models. In the 2nd phase, distributed images dataset is shared with the TL model for training purposes. This process runs till the learning criteria meet. In the 3rd phase, we shared the trained TL model with the cloud server for validation and testing. In this study, we considered a well-reputed dataset of lung cancer classification as a case study to strengthen the proposed model working. The results and simulation are based on this dataset.

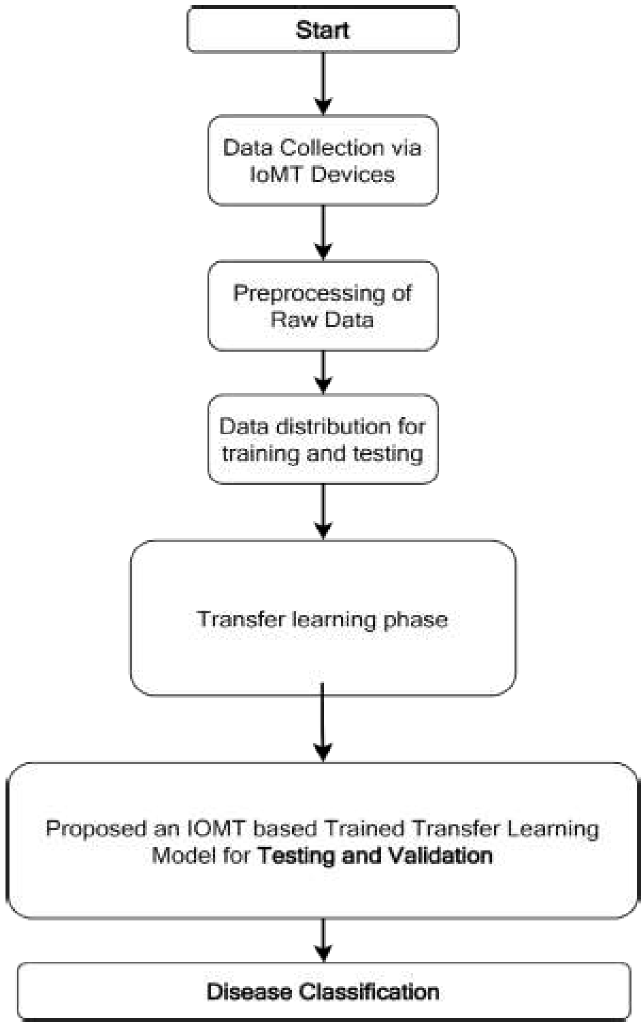

FIGURE 2. Pseudo code of proposed IoMT based transfer learning model.

The majority of the dataset LC25000 consisted of 1250 pathology slides of lung and colon tissues. The lung cancer dataset was improved by rotating & flipping the photographs in various settings, yielding 25,000 images divided into five groups, each of which contained 5000 images. The photos were downsized to 768 $\times$ 768 pixels before smearing the augmentation. A sample of photos from the collection is shown in Figure 3. Each image class in the collection has a name and an ID, as shown in Figure 3.

IV. SIMULATION RESULTS

Transfer Learning (TL) is a DML method for repurposing a model created for one purpose. DML necessitates the creation of a new network architecture from previously trained networks, which is then fine-tuned and applied to a new

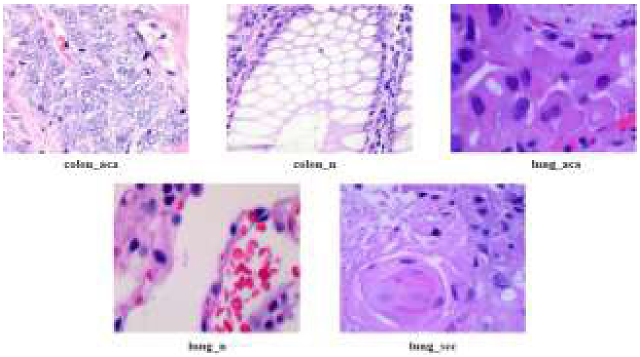

FIGURE 3. Histological images of each class from the dataset.

TABLE 2. Implementation environment.

TOOL/ DEVICE NAME	DESCRIPTION
Desktop System	Windows 10 pro N (Version 21H1)
Processor	Intel(R) Core (TM) i7-4770 CPU @ 3.40GHz 3.40 GHz
RAM	18.0 GB
MATLAB	2020a

dataset using a large dataset. The TL method shortens the time and resources needed to train deep CNNs. It is usually faster and less stressful than building and preparing a network from scratch. TL is frequently implemented using DML models developed for large-scale image grouping projects, such as the ImageNet competition [47] GoogLeNet has been trained on over a million photos and can categories them into 1000 different object categories (such as keyboard, coffee mug, pencil, and many animals). The network has learned rich feature representations for a wide range of images. The network takes an image as input and returns a label for each object in the image and probabilities for each object category. Deep learning applications frequently employ transfer learning. You can utilize a pre-trained network to learn a new task as a starting point. Transfer learning makes fine-tuning a network considerably faster and easier than training a network from scratch with randomly initialized weights. You can quickly transfer learned features to a new assignment with fewer training photos. Due to this reason, we have considered the model for lung cancer image classification with some major changes.

The MATLAB 2020a tool is used for this experiment. The pre-trained model is customized as per the requirements of this research; the first layer and the last three levels of the model are updated. Images were scaled to 227 × 227 × 3 to fit the model's size constraints. The lung cancer dataset was partitioned 70% of the images was set aside for training, and 30% were set aside for validation. Table 2 shows the implementation environment for the simulation. Table 3 shows the training preferences and other factors used for training. These training options and parameters were tested and validated with different considerations and showed the best result in this study.

TABLE 3. Training options and parameters.

Training preferences	Considerations
Size of Image	227*227*3
Number of epochs	04
Iterations per epoch	273
Total iterations	1092
Initial learning rate	0.001
Momentum	0.9
Solver	SGDM
Execution Environment	Auto
Minibatch Size	64
Shuffle	every-epoch
Validation Frequency	1

TABLE 4. Training of proposed IoMT enabled intelligent system for diagnosis of lung cancer disease.

Training results						
		Predicted Class				
	Class ID	1	2	3	4	5
True Class	1	3442	56	02	0	0
	2	2	3498	0	0	0
	3	0	0	3430	02	68
	4	0	0	02	3498	0
	5	0	0	101	0	3399

TABLE 5. Validation of proposed IoMT enabled intelligent system during diagnosis of lung cancer disease.

Validation results						
		Predicted Class				
True Class	Class ID	1	2	3	4	5
	1	1498	2	0	0	0
	2	0	1500	0	0	0
	3	0	0	1477	0	23
	4	0	0	0	1500	0
	5	0	0	66	0	1434

TABLE 6. Performance of proposed IoMT-enabled intelligent system with a trained model.

Class	Accuracy	Misc. Rate	Precision	Sensitivity	Specificity	F1 Score
Training Results						
1	99.66%	0.44	0.98	1.0	0.99	0.99
2	99.67%	0.33	1.0	0.98	0.99	0.99
3	99.07%	0.93	0.98	0.97	0.99	0.98
4	99.98%	0.02	1.0	1.0	1.0	1.0
5	99.09%	0.91	0.97	0.98	0.99	0.98
Validation Results						
1	99.97%	0.03	1.0	1.0	1.0	1.0
2	99.97%	0.03	1.0	1.0	0.99	1.0
3	98.81%	0.19	0.98	0.96	0.99	0.97
4	100%	0.0	1.0	1.0	1.0	1.0
5	98.81%	0.19	0.96	0.98	0.99	0.97

Figure 1 illustrates the recommended methodology. The histopathological images are first taken and transformed to a size of 227 × 227 × 3 according to the model's specifications. The next step is to provide the model-scaled photos for training and validation: the accuracy, misc. The preliminary results' rate, precision, recall, specificity, and F1 score are examined. The confusion matrix of the proposed Secure IoMT-based TL model's performance at the training level is shown in Table 4 & validated in Table 5.

Tables 4 and 5 summarize the accuracy and miss rate at training and validation. The proposed TL algorithm has been applied to the lung cancer images dataset of 25000 images; additionally, this data has been divided into training groups of 70% (17500 images) and 30% (7500 images) for validation: the accuracy of the following metrics, misc. Rate, precision, recall, specificity, and F1-score produce various statistical measurements for comparison and performance. The formulas in Eq. (1) to Eq. (6) are used to calculate these parameters as shown below [47]:

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

$$\text{Misclassificationrate} = \frac{FP + FN}{TP + TN + FP + FN} \tag{2}$$

$$\text{Precision (Pre)} = \frac{TP}{TP + FP} \tag{3}$$

$$\text{Sensitivity (recall)} = \frac{TP}{TP + FN} \tag{4}$$

$$\text{Specificity} = \frac{TN}{(TN + FP)} \tag{5}$$

$$\text{F1Score} = 2 * \left(\frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}\right) \tag{6}$$

The proposed secure IoMT-based TL model predicts outputs as described in Figure 1. The value as per class ID (1) indicates that a lung issue has been discovered with the name "Colon Adenocarcinoma," Class ID (2) indicates that the lung tissue has been discovered with the name "Colon Benign," Class ID (3) indicates that the lung tissue has been discovered with the name "Lung Adenocarcinoma," Class ID (4) indicates that the lung tissue has been discovered with the name "Lung Benign," whereas the Class ID (5) indicates that the lung tissue has been discovered with the name "Lung Squamous Cell Carcinoma."

Table 4 illustrates the suggested TL model prediction for the types of lung cancer disease during the training phase. The 17,500 images are used in training, divided into five categories with class IDs (1-5) of the same size. It is determined that 3442 images are truly positive for Type 1 lung disease, which are closely followed and showed lung type "Colon Adenocarcinoma" issues had been observed. Only fifty-six (56) & two (2) records are incorrectly projected as other classes of lung disease, signaling lung types Colon Benign and Lung Adenocarcinoma issues, respectively. For Class ID 2, it is determined that 3498 images are truly positive for Type 2 lung disease, which are being closely followed and showed lung type "Colon Benign" issues have been observed. Only two (2) records are incorrectly projected as other classes of lung disease, signaling lung types of Colon Adenocarcinoma issues. For Class ID 3, it is determined that 3430 images are truly positive for Type 3 lung disease, which are being closely followed and showed lung type "Lung Adenocarcinoma" issues have been observed. Only two (2) & sixty-eight (68) records are incorrectly projected as other classes of lung disease, signaling lung types Lung

TABLE 7. compares the achieved accuracy of the proposed model with another author's findings in their studies.

Studies	Year	Cancer Type	Category of Images	Model	Acc. (%)
Masood. A, et, al, [55]	2020	LC	CT-I	CNN	97.9
Mehmood et al. [57]	2021	*L&CC	*HI	CNN with CSIP	98.4
Da. Nobrega, RVM et.al, [58]	2020	*LC	*CT-I	SVM_RBF +RestNet50	93.19
Shakeel. PM, et. al, [59]	2020	LC	CT-I	E.M	96.2
Bukhari. S, et.al, [60]	2020	LC	HI	RESNET-50	93.91
Mangal. S, et.al, [61]	2020	LC	HI	CNN	97.0 & 96.0
Hatuwal. BK, et.al, [62]	2020	LC	HI	CNN	97.2
Shakeel. PM, et.al, [63]	2019	LC	CT-I	DL-ITNN	98.42
Proposed Model	**2022**	**L&CC**	**HI**	**Transfer learning**	**98.80**

* Lung Cancer = LC, *Lung & Colon Cancer = L&CC, *Histopathology Images=HI, *CT Image=CT-I

Benign & Lung Squamous Cell Carcinoma issues, respectively. For Class ID 4, it is determined that 3498 images are truly positive for Type 4 lung disease, which are being closely followed and showed lung type "Lung Benign" issues have been observed. Only two (2) records are incorrectly projected as other classes of lung disease, signaling lung types of Lung Adenocarcinoma issues. For Class ID 5, it is determined that 3399 images are truly positive for Type 5 lung disease, which are being closely followed and showed lung type "Lung Squamous Cell Carcinoma" issues have been observed. Only one hundred one (101) records are incorrectly projected as other classes of lung disease, signaling a lung types Lung Adenocarcinoma issue.

Table 5 illustrates the suggested TL model prediction for the types of lung cancer disease during the validation phase. The 7,500 images are used in validation, divided into five categories with class IDs (1-5) of the same size. It is determined that 1498 images are truly positive for Type 1 disease, which are being closely followed and showed lung type "Colon Adenocarcinoma lung" issues have been observed. Only two (02) records are incorrectly projected as other classes of lung disease, signaling lung-type "Colon Benign" issues, respectively. For Class ID 2, it is determined that 1500 images are truly positive for Type 2 lung disease, which are closely followed and showed lung type "Colon Benign" issues have been observed. No records are incorrectly projected as other classes of lung disease. For Class ID 3, it is determined that 1477 images are truly positive for Type 3 lung disease, which are being closely followed and showed lung type "Lung Adenocarcinoma" issues have been observed. Only twenty-three (23) records are incorrectly projected as another class of lung disease, signaling a lung type "Lung Squamous Cell Carcinoma." For Class ID 4, it is determined that 1500 images are truly positive for Type 4 lung disease, which are being closely followed and showed lung type "Lung Benign" issues have been observed. No records are incorrectly projected as other classes of lung disease. For Class ID 5, it is determined that 1434 images are truly positive for Type 5 lung disease, which are being closely followed and showed lung type "Lung Squamous Cell Carcinoma" issues have been observed. Only sixty-six (66) records are incorrectly projected as other classes of lung disease, signaling lung type "Lung Adenocarcinoma" issues. Table 6 presents the overall confusion metrics performance in the training phase & validation phase. The comparison of the proposed work with other works related to cancer disease is shown in Table 7.

V. CONCLUSION

Predicting human diseases, particularly cancer, is difficult to provide better and more timely treatment. Cancer is a potentially fatal disease that affects numerous organs and systems in the human body. An IoMT-enabled intelligent system for the healthcare industry 5.0 is being developed to predict cancer disease quickly and accurately without jeopardizing patient privacy. A deep ML model and a secure IoMT-based

TL technique are used to achieve a faster reaction time and higher accuracy rate. Based on the types of lung cancer, the proposed method correctly predicted whether or not a patient had lung cancer. The proposed IoMT-enabled intelligent system for the healthcare industry 5.0 with a secure IoMT-based TL model is simulated using MATLAB 2020a. The proposed IoMT-enabled intelligent system for the healthcare industry 5.0 with TL methodology achieved 98.80%, outperforming the previous best lung cancer disease prediction methods in the smart healthcare industry 5.0.

CONTRIBUTION AND FUTURE WORK

Many recommendation systems for healthcare are already proposed in recent research. The significant contribution of this research is to enrich the healthcare industry 5.0 with IoMT enabled intelligent system for the best prediction of lung cancer disease. We have collected the 'patients' data through IoMT devices or sensors of each patient. After collecting the records of each patient of each hospital, preprocessing is applied to remove noisy data to enrich the healthcare dataset. The transfer learning approach with deep machine algorithms works accurately and produces better results in larger healthcare datasets with ' 'patient data privacy. Finally, we have developed an IoMT-enabled intelligent system for the healthcare industry 5.0 with a secure IoMT-based TL approach for predicting lung cancer. The overall performance of our proposed IoMT-enabled intelligent system achieves 98.80% accuracy.

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