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Review

Symmetry in Privacy-Based Healthcare: A Review of Skin Cancer Detection and Classification Using Federated Learning

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Abstract: Skin cancer represents one of the most lethal and prevalent types of cancer observed in the human population. When diagnosed in its early stages, melanoma, a form of skin cancer, can be effectively treated and cured. Machine learning algorithms play a crucial role in facilitating the timely detection of skin cancer and aiding in the accurate diagnosis and appropriate treatment of patients. However, the implementation of traditional machine learning approaches for skin disease diagnosis is impeded by privacy regulations, which necessitate centralized processing of patient data in cloud environments. To overcome the challenges associated with data privacy, federated learning emerges as a promising solution, enabling the development of privacy-aware healthcare systems for skin cancer diagnosis. This paper presents a comprehensive review that examines the obstacles faced by conventional machine learning algorithms and explores the integration of federated learning in the context of privacy-conscious skin cancer prediction healthcare systems. It provides discussion on the various datasets available for skin cancer prediction and provides a performance comparison of various machine learning and federated learning techniques for skin lesion prediction. The objective is to highlight the advantages offered by federated learning and its potential for addressing privacy concerns in the realm of skin cancer diagnosis.

Keywords: lightweight network; image processing; privacy-aware machine learning; federated machine learning; skin cancer prediction; melanoma skin cancer; deep learning; healthcare

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Citation: Yaqoob, M.M.; Alsulami, M.; Khan, M.A.; Alsadie, D.; Saudagar, A.K.J.; AlKhathami, M.; Khattak, U.F. Symmetry in Privacy-Based Healthcare: A Review of Skin Cancer Detection and Classification Using Federated Learning. *Symmetry* **2023**, *15*, 1369. https://doi.org/10.3390/sym15071369

Academic Editors: Tomohiro Inagaki and Jun Xu

Received: 21 May 2023
Revised: 13 June 2023
Accepted: 3 July 2023
Published: 5 July 2023

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1. Introduction

Artificial intelligence (AI) is the process of making machines mimic human thinking for solving real-world problems by means of intelligent computer programs. Machine learning (ML) is a branch of artificial intelligence that allows computers to learn from data and make predictions or judgements without explicit programming. The ML-based learning process is categorized as supervised, unsupervised, or semi-supervised learning. The goal of ML-based systems is to deduce knowledge from scrutinized data to maximize the possibility of problem solving. A paradigm of ML known as reinforcement learning has emerged, which is the process of enabling a computer to perceive its surroundings and act accordingly to maximize the possibility of goal attainment.

Medical imaging data can be efficiently analyzed for improved illness detection, personalized treatment planning, and other applications of ML in healthcare that can improve patient outcomes and develop precision medicine. Large-scale patient data can be analyzed by ML algorithms, assisting in disease early detection, risk prediction, and clinical workflow optimization, supporting healthcare personnel in making wise decisions, and enhancing overall healthcare delivery. Health is not simply a lack of illness, although it is described as a combination of mental, physical, and social well-being. Healthiness is a crucial aspect of improving people's quality of life. However, the global health problem has become a challenge due to various factors, including the limited availability of physicians and nurses during critical times, significant disparities between rural and urban areas, and inadequate healthcare services. The health of people is strongly associated with their daily life activities. Over two hundred distinct kinds of cancer have been identified. Cancer is a disease characterized by the uncontrolled proliferation of abnormal cells with the potential to metastasize, or spread, to other parts of the body. Cancer accounts for approximately one in six deaths worldwide [1]. Skin cancer is one of the most serious types of cancer. When caught early, skin cancer is very treatable. Human skin is important because it protects the internal organs and underlying structures of the body, such as the muscles and bones. An important role is played by the skin since even a minor disruption in its function can have far-reaching consequences for the body's systems. A lesion region is the term used to describe a skin lesion. Lesions on the skin can range in appearance and severity. The many types of skin cells that contribute to the development of each lesion are used to categorize them. Melanocytes, the cells responsible for producing the protein pigment melanin, are damaged or destroyed in melanocytic diseases such as melanoma [2].

Melanoma is the most lethal kind of skin cancer out of about 200 different types. Clinical screening is the first step in diagnosing melanoma, followed by dermoscopy and histopathology. When caught early, melanoma is an almost universally curable form of skin cancer. Melanoma is diagnosed by first physically inspecting the damaged area of skin to rule out other possible causes. According to global statistics, there would be around 10 million cancer-related fatalities in 2020 [3]. High-resolution camera images of skin lesions taken by dermatologists are called dermatoscopic images, and they have an accuracy of 65–80 percent in the diagnosis of melanoma without any extra technical support. Melanoma diagnostic accuracy increased from 50% to 75% with the addition of dermatoscopic pictures and closer visual inspection by cancer treatment professionals.

In the traditional healthcare system, there is a focus on centralized agents who are responsible for providing raw data. As a result, this system still has significant risks and problems. Security and privacy are two of the most critical concerns. When combined with artificial intelligence (AI), the system would consist of several agent collaborators capable of successfully conversing with their intended host. The biological data contain patient-specific information, such as data linked to heart activity, brain activity, respiration reaction, facial expressions, blood activity, skin response, and several other vital signs. This type of data raises grave privacy concerns since it may be collected in a national-level research endeavor, which poses a potential national privacy danger as well as a violation of individual privacy.

Recently, a number of data protection laws have been enacted globally in an effort to address data privacy concerns. One such example is the European Union's implementation of the General Data Protection Regulation (GDPR) [4] to safeguard the privacy of user data. GDPR aims to protect individual data privacy and ensure data security, while also ensuring that companies or businesses that violate the regulation will face harsh fines. Comparable measures are implemented by China with the China Cyber Security Law [5], the United States with the California Consumer Privacy Act (CCPA) of 2018 [6], and numerous other nations with similar laws. The traditional machine learning-based methodologies require the training data to be centralised. Consequently, these strategies necessitate the collection of data from numerous sensors, which incurs a larger computational cost as these models can only be trained on enormous datasets. As biological data contain patient-specific information, which is a major privacy problem, and the current privacy rules, such as

GDPR, CCPA, the China Cyber Security Law, and many more, have created a formidable obstacle for standard machine learning algorithms.

Using data from multiple institutions is a viable option for reducing the present class imbalance and expanding the annotated dataset. However, exchanging medical records between institutions is difficult due to privacy, technical, and regulatory concerns. Secure and privacy-preserving machine learning has the ability to bring patient data protection and data use for research and clinical routines closer together. Google has recently proposed federated learning to circumvent these obstacles [7]. Another intriguing function that operates in a decentralized fashion is federated learning (FL). It keeps the desired system's model-based communication going without moving the underlying data. Consequently, federated learning consumers will obtain personalized machine learning while also addressing privacy concerns. Some of the healthcare system's constraints and difficulties may be alleviated with the help of a hybrid approach involving FL and AI. The overall model is trained in a distributed fashion: client sites regularly communicate local client updates to a central server to develop a global model; the central server combines the updates and returns the parameters of the updated global model.

The development of a privacy-aware healthcare system for skin cancer detection and classification is needed. The objective of this review is to provide insight on the effectiveness of traditional machine learning approaches for skin cancer diagnosis and how federated learning techniques can be adopted for the development of privacy skin cancer prediction healthcare. A review is provided based on the latest research articles in the fields of machine learning and federated learning.

The contributions of this study are as follows:

- The application of federated learning in the context of skin cancer detection and classification is reviewed in detail in this work. It provides a thorough overview of the available literature, summarizing the major contributions and methods used.
- The importance of privacy in healthcare is highlighted in this study, especially when it comes to the identification and classification of skin cancer. It investigates how federated learning might overcome privacy issues by facilitating cooperative model training without disclosing private patient information.
- The research applies symmetry-based analysis to examine how well skin cancer can be detected while maintaining privacy. It talks about how federated learning is symmetrical, putting an emphasis on how different institutions can participate equally while still ensuring data privacy.
- In this study, federated learning is evaluated to detect and classify skin cancer using a variety of methodologies and techniques.
- The research identifies the fundamental challenges and limitations of federated learning for skin cancer detection and classification in its current form. It explores possible future research directions, such as the creation of more efficient communication protocols, improved model aggregation approaches, and dealing with variability in data sources.

The organization of this paper is as follows: The research methodology for effective analysis of the existing literature is described in Section 2. Section 3 provides an overview of federated learning and its adoption in the healthcare system. Section 4 provides a review of the solutions developed based on traditional machine learning for skin cancer prediction, and Section 5 provides a review of federated learning algorithms developed for skin cancer detection and classification. Research challenges for federated learning in skin cancer are discussed in Section 6, and the conclusion of this review paper is discussed in Section 7.

2. Research Methodology

The goal of this systematic literature review was to identify and categorize the best existing approaches to skin cancer detection using classical machine learning, as well as examine data privacy challenges and potential privacy-aware solutions employing federated learning. The collected data from primary sources is organized and analyzed in a systematic manner. Conducting a thorough literature review enables the research to provide a logical, coherent, and robust answer to the following research questions:

Question # 1: What are the implications of data privacy in healthcare?
Question # 2: What are the common datasets for skin cancer detection?
Question # 3: What are the major machine learning-based techniques for skin cancer prediction?
Question # 4: What are the federated learning-based techniques for skin lesion detection?

Hence, the articles selected for inclusion in this review were carefully examined to ensure a comprehensive and thorough understanding of their contents. To extract the necessary and pertinent data, we employed specific criteria during our search process:

- Identification of search keywords or terms aligned with the research questions.
- Inclusion of words closely associated with the selected keywords.
- Formulation of search strings using logical operators to connect the search terms.

The combination of keywords for search strings is listed below in Table 1. Additionally, the search terms were carried out using the logical operators "AND" and "OR" between combinations of the keywords.

Table 1. Search selection and combination of keywords.

Term	Combination of Keywords
Skin Cancer	Skin disease, skin cancer, skin lesion, treatment of the skin, skin cancer types
Machine Learning	Machine learning, deep learning, neural networks, deep neural networks, machine learning skin cancer, machine learning skin lesion
Artificial	Artificial intelligence, artificial neural network, artificial neural network, skin cancer
Federated	Federated learning, deep federated learning, decentralized federated, asynchronous federated, federated skin cancer, federated skin lesion
Privacy	Privacy-aware learning, privacy-aware machine learning, privacy issues, skin cancer privacy
Healthcare	Healthcare privacy, healthcare machine learning

The most pertinent publications that fit with the goal of this systematic analysis were chosen using a selection process. Specific criteria, such as the language of the paper, its publication year, and its applicability to the intended topic, were used to determine the initial inclusion of research papers and conference papers. For inclusion in this study, only works of research written in English were taken into consideration. We performed our initial search on reputable scientific databases, including IEEE, Elsevier, ACM, Springer Nature, MDPI, and Google Scholar, to gather pertinent information regarding skin cancer detection. Our review paper specifically examined research published from 2011 to 2023. The selection of papers was based on their relevance to the search terms. The initial search resulted in 1508 journal articles and conference papers. A total of 108 publications from the identified ones were first picked based on their titles and their applicability to our research. Then, 62 research publications that were deemed relevant after a more thorough review of the abstracts were chosen. To facilitate further research, a thorough examination of these chosen papers was conducted.

3. Federated Learning: Privacy-Aware Learning in Healthcare

The integration of machine learning (ML)-based techniques in a digital healthcare system allows healthcare service providers (HSPs) to develop intelligent, effective, and early disease diagnosis solutions in healthcare applications. Technological advancements such as the Internet of Medical Things (IoMT) enable real-time patient monitoring, and thus the HSP can evolve towards real-time intelligent healthcare solutions. ML and IoMT-enabled healthcare systems require the training data to be in centralized form. Hence, these techniques require data to be collected from various devices, and this also has a higher computational cost as these models can only be trained on huge datasets. As the biomedical data have personalized information about the patient, which is indeed a big privacy concern, and the current privacy regulations, such GDPR, CCPA, the China Cyber Security Law, and many others throughout the world, have created a huge challenge for traditional machine learning techniques. The existing ML and IoMT-based healthcare systems require the patient data to be centrally trained in the cloud, and the results are then disseminated to the client end. A typical setting of the existing systems is illustrated in Figure 1.

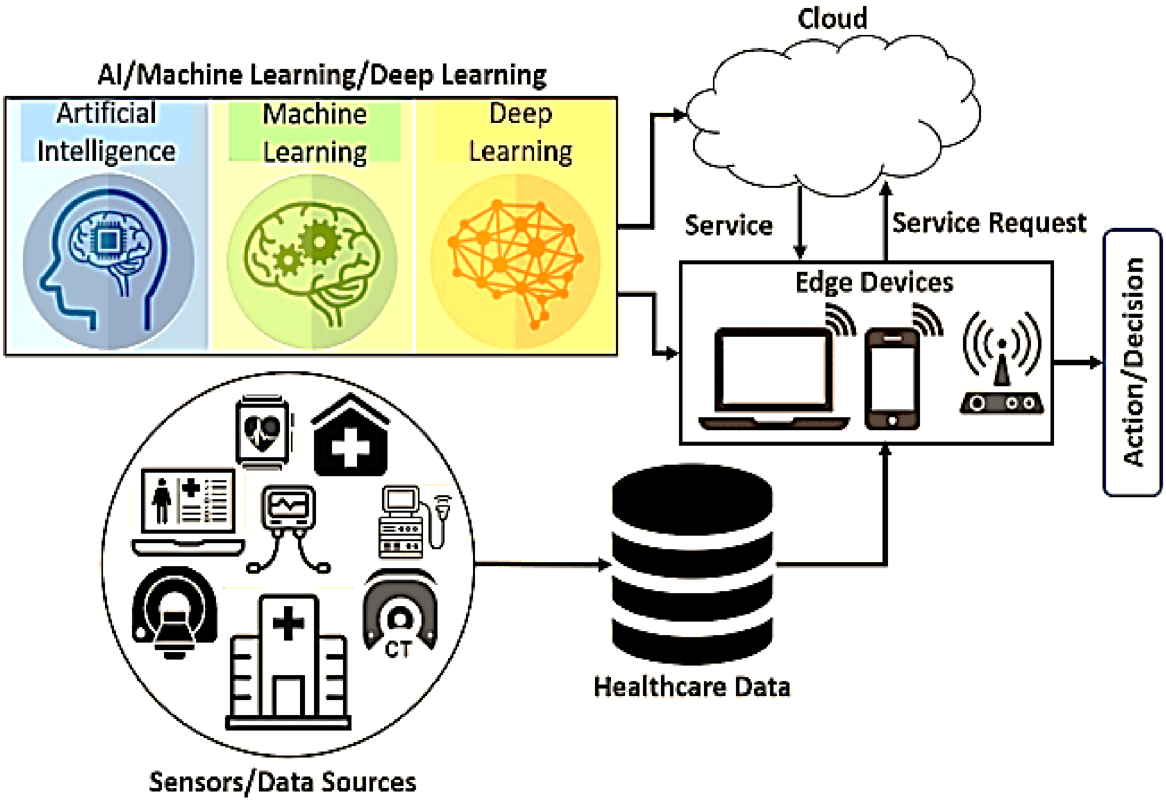


Figure 1. Overview of the intelligence-based healthcare service provider system.

Federated learning (FL) was recently proposed [7,8] to overcome the data privacy issues. By retaining the data on the device, FL aims to establish a privacy-aware collaborative machine learning method with shared models. As a result, federated learning users will benefit from individualised machine learning that also addresses privacy concerns. This federated learning model also overcomes the communication efficiency issue by using the Federated Averaging (FedAvg) algorithm, which significantly reduces the communication to train the model. The federated learning works in the way that initially the devices will receive the current model from the cloud, after which the device will improve this model using local data on the device, and then updates to the model are shared with the cloud using encryption. After receiving the updates from the devices, the cloud immediately updates the global model using FedAvg and then shares this with the client devices. The client devices only share the model with the cloud; all the training data remains on the device, and the cloud does not store the individual updates. The working mechanism of the standard FedAvg algorithm is illustrated in Algorithm 1.

Algorithm 1: FedAvg-based decentralized and collaborative learning model [7].

Working at cloud end:
initialize ω_o
for every round $r = 1, 2, \ldots$ **do**
$m \leftarrow$ *maximum of* (C. K, 1)
$S_r \leftarrow$ (random m number of clients)
for every client $m \in S_r$ **do in parallel**
$\omega^m_{r+1} \leftarrow$ ClientEnd(m,ω_r)
$\omega_{r+1} \leftarrow \sum_{m=1}^{K} \frac{n_m}{n} \omega^m_r + 1$
Working at ClientEnd(m, ω)**:** //For every mth client
$\beta \leftarrow$ (fragment each P_k to groups of β size)
Each local epoch **do**
fragment β **do**
Compute gradient descent on the weights
return model updates to cloud

This FedAvg algorithm works in the following steps, and each is described as follows:

Step-1: An initial training model ω_o is obtained from the HSP cloud by each HSP client node.
Step-2: Client nodes, upon receipt of ω_o, perform training on local training data, which is fragmented into β-sized batches and returns an update of weights ω in the local model to the HSP cloud.
Step-3: HSP cloud, upon receipt of ω_k from the m number of clients, performs aggregation of the received weights. After that, an averaging of all the received updates and a new updated global model ω_{r+1} are then returned to the m client nodes.
Step-4: This communication between the clients and the cloud is continued until no further evolution in the client data is experienced.

The global privacy laws hinder the working and performance of these traditional intelligence-based healthcare systems because they do not address the data privacy of patients. To address the privacy concerns in the healthcare service provider system, a FL-based system is necessary, as illustrated in Figure 2.

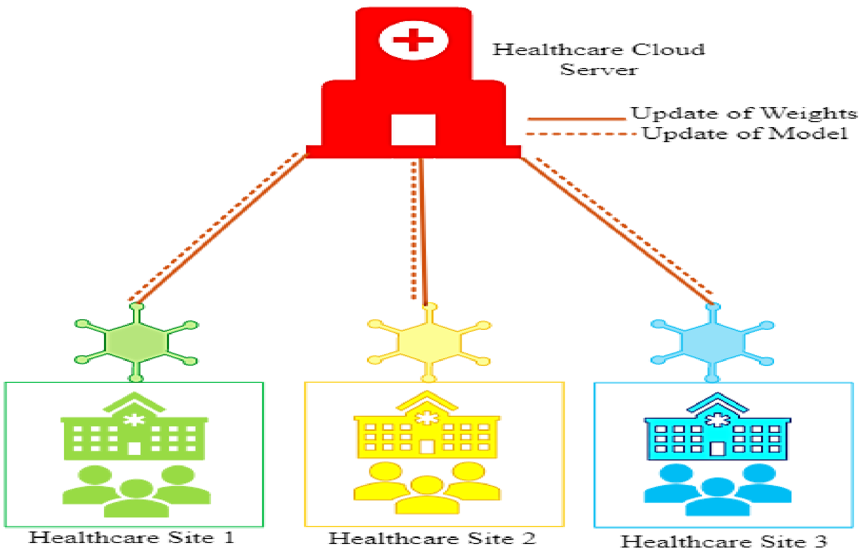


Figure 2. Federated learning enabled healthcare service provider system.

Additionally, in the FL-enabled HSP system, all the training of patients personalized data is performed at the local client healthcare site, which enables the HSP to develop a privacy-aware solution as the data never leaves the client healthcare site. One such adoption of the FL-based healthcare model for effective cardiovascular disease prediction is proposed in [9]. The FL-based healthcare system will require the cloud end to aggregate all the local model updates from the client and then, based on the FL cloud model, update the global model. This updated global model is then disseminated to the HSP clients, and after each round of communication, the clients will learn a new global model until there is no further evolution.

To further improve the convergence and communication efficiency of the FedAvg, the authors in [10–16] have proposed updated variants of FL. The authors of [10] suggest an improved version of FedAvg with the aim of improving the precision and convergence rate of the cutting-edge federated learning algorithm. To implement Bayesian nonparameterized approaches for heterogeneous data, they introduced the Federated Match Averaging (FedMA) algorithm, which is based on the layer-wise federated learning algorithm. Their suggested FedMA outperforms FedAvg in terms of convergence, accuracy, and communication size reduction. The authors in [11] suggested a fast-convergent technique that accomplishes intelligent selection of each device at each round of training the model in order to maximise the convergence speed of federated learning. To increase the convergence rate, their approach employs precise and efficient approximations for the transmission of a nearly optimum distribution of device selection. On the server end of learning, their suggested method uses an aggregate mechanism rather than straightforward averaging. Their aggregation method takes into account the system heterogeneity of the diverse current mobile network devices.

The authors in [12] have presented a method that allocates weights in accordance with the contribution of each class to the local models since the existing federated learning technique can degrade the aggregation of local models. They proposed a lightweight aggregation method to improve the training of models, resulting in better communication efficiency. They developed class-weighted aggregation techniques using federated learning for non-independent and identically distributed (non-IID) data with the aim of further improving communication efficiency. Their proposed method reallocates the weights according to the respective classes and uses weighted average-based aggregation, which is less complex and easily implementable. Their federated learning with class-weighted aggregation (FedCA) uses two aggregation methods for training distributed data (FedCA-TDD) and validation set accuracy (FedCA-VSA).

A blockchain-based approach based on FL was suggested by the authors in [13] to address the problem of data privacy for an IoMT-based healthcare system. They employ blockchain for federated learning model verification and homomorphic encryption to solve the problem of user data privacy with their suggested FL-EM-GMM (Federated Learning Expectation Maximization Gaussian Mixture Model Algorithm). Their suggested approach demonstrates that IoMT data training may be carried out utilising local privacy to stop data leakage. Comparing their FL-EM-GMM algorithm to conventional machine learning techniques reveals increased security, usability, and efficiency.

IoMT devices are low-power, lightweight sensor devices with limited energy backup. Consequently, to reduce energy consumption, IoMT sensors are a prominent requirement. The authors in [14] have proposed a federated learning-based technique to overcome the issue of energy consumption. They formulated an iterative algorithm and closed-form techniques for the allocation of time and bandwidth. Meanwhile, reiterative procedures necessitate a preliminary viable solution; they constructed the minimization of time problem, and they proposed a bisection-based algorithm, which provides an achievable resolution. Their proposed algorithm utilizes 59.5% less energy as compared to the conventional method. The authors in [15] have proposed a technique based on FedAvg to enhance the energy efficiency and heterogeneity of IoT devices. Their extension of the FedAvg algorithm is dependent on a weight-based proximal term, and their algorithm allows a limited number of IoMT users to participate in each round of model training in an unbiased sampling manner. Their proposed algorithm overcomes the issue of energy consumption as compared with traditional techniques.

The prediction of human activity such as heart rate using wearable IoMT devices profits users. Traditionally, the cloud/server collects sensed data from IoMT devices and then performs the prediction of that sensed data. Nevertheless, this traditional technique has significant privacy concerns and requires sensed data to be located at a central location for the purpose of model training and prediction. The authors of [16] suggested a Bayesian inference-federated learning with autoregression with exogenous variables (ARX) model to construct a privacy-aware heart rate prediction approach. In comparison to conventional machine learning models, the FedARX technique achieves precise and reliable heart rate prediction. Table 2 summarizes the accomplishments of each FL method discussed in this section.

Table 2. Summary of FL-based algorithms and their achievements.

Method	Task	Accomplishments
FedAvg [7]	Privacy-preserving decentralized collaborative learning	Provides privacy preserving based technique for machine learning applications.
FedMA [10]	Optimization of the federated learning model	Performs better than the baseline FedAvg algorithm.
FOLB [11]	Optimizing the convergence speed	Improved model accuracy, model stability, and convergence speed.
FedCA [12]	Improved aggregation for federated learning	Improves communication efficiency and aggregation using two class-weighted aggregation techniques.
FL-EM-GMM [13]	Blockchain-based federated learning	Improves data privacy and federated model verification using blockchain technology for healthcare.
Iterative-FL [14]	Energy efficiency	Reduces energy consumption using the iterative solution for federated learning.
FedAvg-Extension [15]	Resource allocation and energy efficiency	Improves resource allocation and reduces energy consumption.
FedARX [16]	Heart rate prediction	Improves accuracy and robustness for heart rate prediction.

4. Skin Cancer Detection and Classification: Traditional ML Methods

Skin cancer is one of the most serious types of cancer. When caught early, skin cancer is very treatable. Human skin is important because it protects the internal organs and underlying structures of the body, such as the muscles and bones. An important role is played by the skin since even a minor disruption in its function can have far-reaching consequences for the body's systems. Typical examples of human skin cancers are depicted in Figure 3. This figure shows eight types of skin cancers: Melanoma (MLA), Basal cell carcinoma (BCC), Squamous cell carcinoma (SCC), Vascular lesion (VLN), Melanocytic nevus (MCN), Benign keratosis (BGK), Actinic keratosis (ATK), and Dermatofibroma (DFA).

- **MLA:** It is an aggressive form of skin cancer arising from melanocytes, the cells responsible for melanin production. It is characterized by the presence of irregular or evolving moles or spots on the skin. If left untreated, melanoma can metastasize to distant organs.
- **BCC:** It is the most prevalent type of skin cancer, typically presenting as small, pearly nodules or pinkish patches on the skin. BCC grows slowly and rarely spreads beyond the local area, but it can cause damage if left untreated.
- **SCC:** It originates from the squamous cells, the outermost layer of the skin. It often appears as scaly or crusty growths, persistent sores, or red, inflamed patches. If not detected and treated early, SCC can metastasize to other parts of the body.
- **VLN:** This encompasses abnormal growths or abnormalities in blood vessels, such as hemangiomas or angiokeratomas. They may manifest as red or purple birthmarks, port-wine stains, or other vascular malformations on the skin.

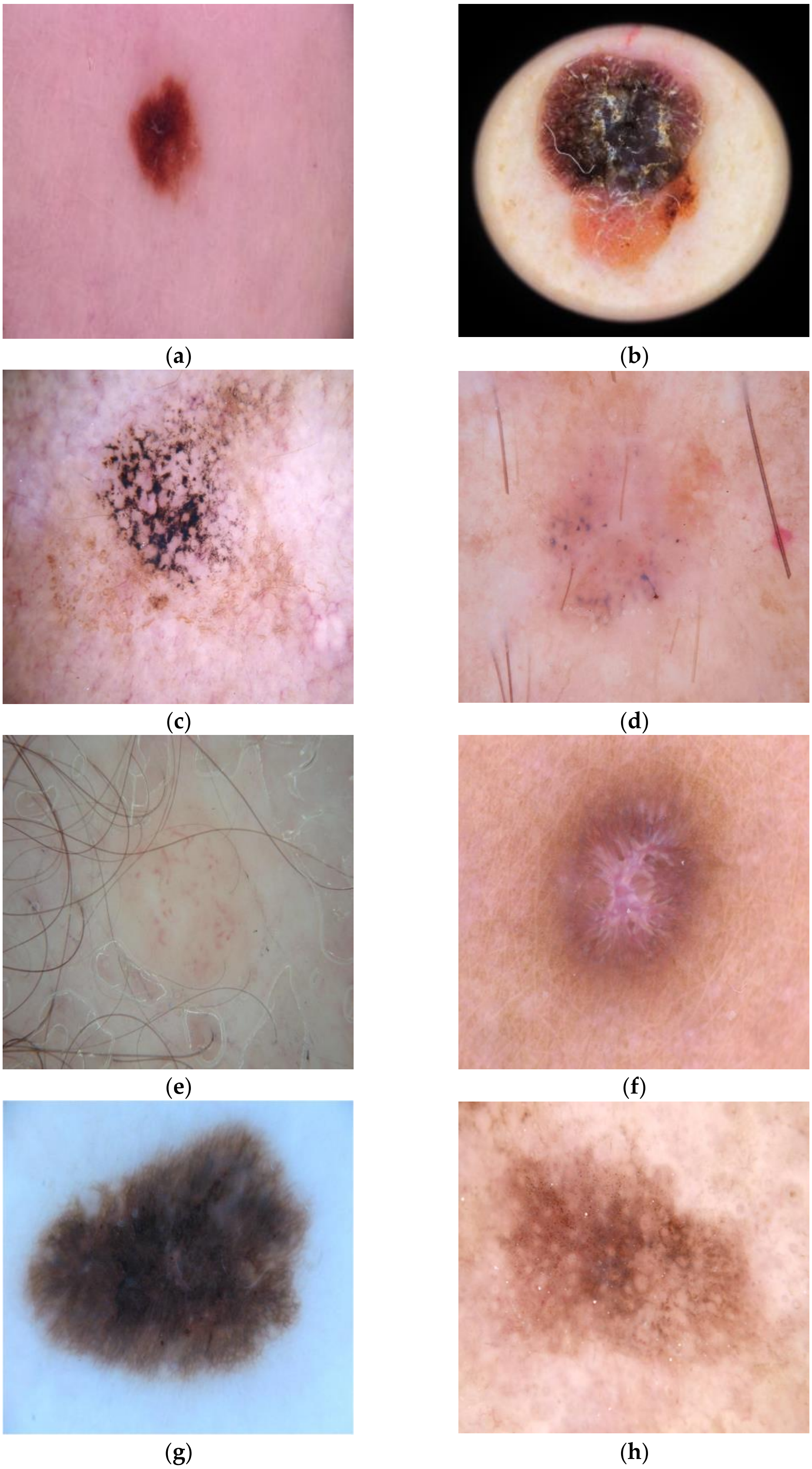
- **MCN:** These, commonly known as moles, are benign skin growths that typically exhibit a brown or black coloration. Moles can be flat or raised, and their size and shape can vary. While most moles are harmless, some may transform into melanoma or display changes necessitating medical attention.
- **BGK:** It encompasses non-cancerous growths resulting from excessive skin cell production. They often manifest as rough, scaly patches on the skin, such as seborrheic keratoses or actinic keratoses. Although benign, certain forms of keratosis can progress to squamous cell carcinoma if left untreated.
- **ATK:** Arises due to chronic exposure to ultraviolet (UV) radiation from the sun or artificial sources. These lesions typically appear as rough, scaly patches on sun-exposed areas of the skin. If left untreated, actinic keratosis can progress to squamous cell carcinoma.
- **DFA:** It represents benign skin growth commonly found on the legs. They present as firm, reddish-brown bumps that can be tender or itchy. While generally harmless, dermatofibromas may resemble other skin conditions and should be evaluated by a dermatologist if any concerns arise.

A new field of study has been created for the early identification of cancer thanks to the use of ML for cancer detection and classification, which has been demonstrated to diminish manual system deficiencies. In the ML-based skin cancer detection system, the algorithm is required to be trained, tested, and validated on a dataset. The commonly used datasets in ML algorithms for skin lesion detection and classification are listed in Table 3. An international challenge for the detection of skin lesions, namely the International Skin Imaging Collaboration (ISIC), is open every calendar year for researchers around the globe.

Table 3. Common datasets for skin cancer prediction.

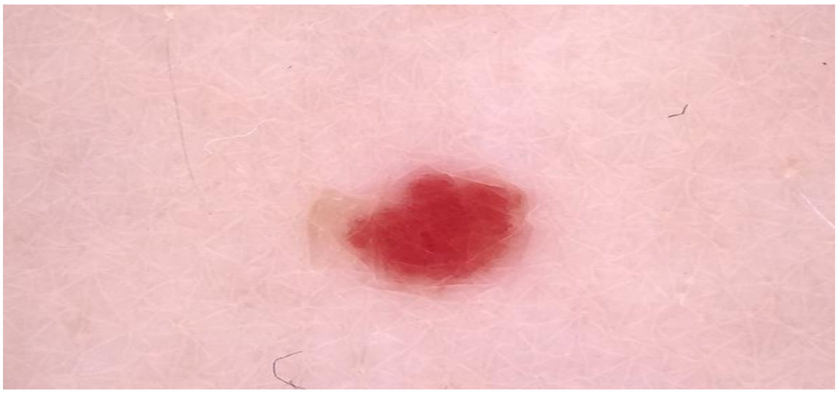
Dataset	Attributes
ISIC 2016 [17]	900 training and 379 testing images
ISIC 2017 [18]	2000 training and 600 testing images
ISIC 2018 [19]	12,500 training and 2000 testing images
ISIC 2019 [20]	25,331 training images and 8238 testing images
ISIC 2020 [21]	33,126 training images and 10,982 testing images
HAM10000 [22]	10,015 skin lesion images
BCN20000 [23]	19,424 skin cancer images
Dermofit [24]	1300 high-resolution images
PH2 [25]	200 dermoscopy images
SKINL2 [26]	376 light field images
SynthDerm [27]	2600 melanoma skin images
DeepLesion [28]	32,735 lesions in 32,120 CT slices from 4427 patients

ML algorithms require training, testing, and validation on a dataset. The authors of [29] examine the promise of ML and AI in identifying various forms of skin cancer as well as the difficulties associated with using ML and AI, such as safeguarding user data and training algorithms. In [30], the authors introduce several machine learning and image processing techniques for detecting and classifying cancer. Since the support vector machine (SVM)-based method achieved 96% accuracy, it was recommended as the superior classification approach. The authors of [31] developed a system to classify and predict skin cancers, which may be applied to the many different types of skin lesions that exist. The authors also discuss how dermatologists contributed to the ML model creation process.



(a) (b) (c) (d) (e) (f) (g) (h)

Figure 3. *Cont.*



(**i**)

Figure 3. Skin cancer types in humans. (**a**) Melanoma. (**b**) MLA Malignant type. (**c**) Actinic keratosis. (**d**) Basal cell carcinoma. (**e**) Benign keratosis. (**f**) Dermatofibroma. (**g**) Melanocytic nevus. (**h**) Squamous cell carcinoma. (**i**) Vascular lesion.

In [32], the authors examine the prediction accuracy of several different types of conventional AI-based approaches for the detection of skin cancer. They mostly employ algorithms in this context. The diagnostic accuracy results demonstrated a wide range, with fair sensitivity for melanoma but significantly less for keratinocyte carcinomas. In [33], the authors focus mostly on leveraging mobile health to identify cancer. There are several worries about privacy and accuracy in the field of mobile health. They describe an on-device inference App and use a dataset of skin cancer photos to prove the notion, addressing the difficulties inherent in mHealth apps. With 10,015 skin cancer photos, they employ a Convolutional Neural Network model that has already been trained. According to [34], a hybrid approach was employed to identify melanoma malignancy. This technology makes cancer detection much simpler for doctors and laypeople alike. Convolutional neural networks, together with two traditional machine learning classifiers, are used for this detection, significantly boosting the system's overall performance. It is well known that dermoscopy images often contain artefacts; hence, the authors in [35–37] introduced their work on a method to detect and quantify shortcut learning in trained classifiers for skin cancer diagnosis. To train a skin cancer classifier, they use a typical VGG16 architecture and assume that color calibration charts (colored patches) only appear in healthy skin scans. They employ a neutralization technique that is model-agnostic for this purpose. The authors of [38] want to provide a dynamic training and testing enhancement that will lead to noticeable performance gains. As opposed to a traditional search method, which would need to train a new model each time an augmentation was offered, the searching augmentation framework employed in this study only requires a fraction of the GPU hours. Bayesian optimization on a trained model is used to speed things up while also improving performance.

Furthermore, the authors of [39] propose a smart Region of Interest (ROI)-based approach for distinguishing melanoma from nevus cancer, making it easier to identify skin cancer with the use of transfer learning. A convolutional neural network (CNN)-based transfer learning model with data augmentation was utilized for this objective. In [40,41], the authors tackle the issue of how to identify skin cancer by exploring the potential gains of merging human and artificial intelligence for skin cancer categorization. One CNN was trained using a variety of deep learning methods. An enhanced VGG-16 transfer learning-based method is proposed in [42] to overcome the issues of skin cancer classification and the accuracy of the model. The authors considered the dataset containing dermoscopy images of malignant and benign types of skin cancer classes. Their enhanced method was able to achieve higher prediction accuracy with a lesser consumption of local number of epochs, resulting in better prediction accuracy and a faster response time from the health service provider.

To further enhance the skin lesion analysis, several ML-based methods are introduced. In [43], a Social Group Optimization (SGO)-based technique is proposed for the evaluation and segmentation of melanoma skin dermoscopy images. An improved lesion image extraction method is proposed in [44], which uses a combination of multi-scale morphological local variance reconstruction and fast fuzzy C-means clustering. Improved skin cancer prediction methods are developed by researchers such as an all-inclusive application [45], combination of adaptive region growth and neuromorphic clustering [46], hybrid meta-heuristics for enhance image boundaries estimation [47], DL-based technique BF2SkNet for optimal feature [48], deep neural network with features fusion and selection [49], hybrid deep whale optimization with entropy-mutual information (EMI) method [50], enhanced classification technique [51], modified meta-heuristic technique for feature selection [52], a hybrid classification method with feature optimization [53], enhanced cost estimation using adaptive multi-cost function [54,55], and an optimal feature extraction using the Henry Gas Solubility Optimization (HGSO) algorithm [56].

5. Skin Cancer Detection Using FL: A Privacy-Aware Approach

FL provides a privacy-aware machine learning environment for healthcare service providers. Recently, FL-based detection of skin cancer has been proposed [57–61]. Skin cancer detection in a FL-based distributed learning environment is different as compared to traditional machine learning settings. FL-based implementation requires the learning process to be in two folds, i.e., server-end and client-end. For effective skin cancer detection, learning models both at the client and server must be designed in such a way that they enable effective detection of the skin lesion from dermoscopy images while data privacy remains intact. FL is a recently developed research domain, and there are only a few researchers who have demonstrated the implementation of FL for effective skin lesion detection. For the implementation of FL algorithms in a healthcare service provider environment for skin cancer detection and classification, a conceptual architecture is depicted in Figure 4.

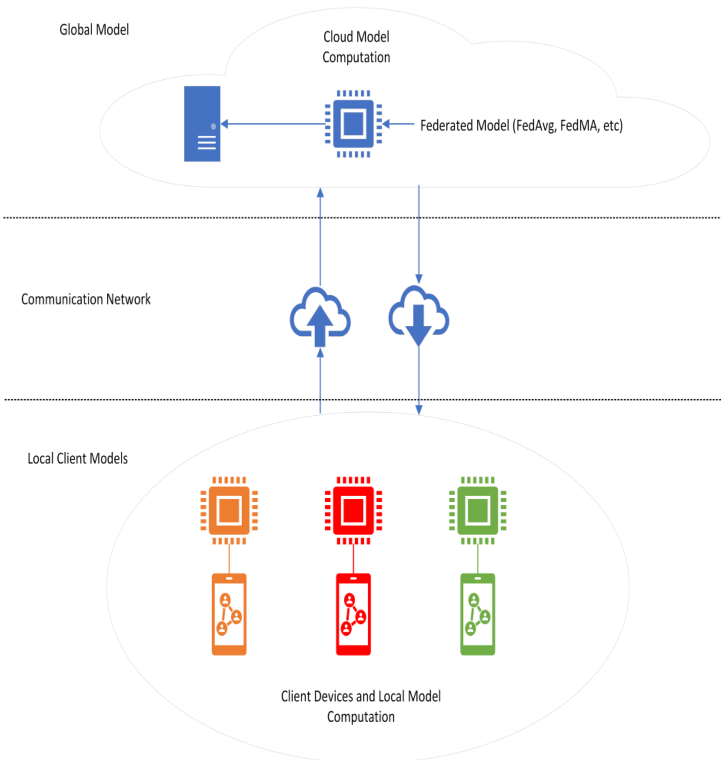


Figure 4. Conceptual architecture of FL adoption for skin cancer prediction.

The authors in [57] proposed a CNN-based adaptive implementation of FL to detect skin disease from dermoscopy images. For the global model (server end), they utilized an adaptive ensemble CNN averaging mechanism. For the client end, the authors implemented the ensemble CNN with a gradient model. Their proposed method achieved 95% accuracy in stable conditions and 89% accuracy with complex data. The authors tested their method on the International Skin Imaging Collaboration (ISIC) 2019 dataset.

Skin melanoma cancer detection using FL is proposed in [58]. The authors multimodal (MM) technique compromising of skin lesion images with the corresponding patient's clinical data. Authors fine-tuned their model and can achieve 3.3% higher sensitivity as compared to the central (traditional) learning mechanism. In the field of medical imaging, the performance of both the CNN for classification and the FL strategy for data privacy protection is astounding. The authors in [59] created a customized dermoscopy image dataset with four classes of skin diseases, proposed a CNN model, compared it to different benchmark CNN algorithms, and tested a federated learning technique to maintain data privacy. To increase the dataset and broaden the model, an image augmentation approach was used. Their model performed better in the FL-based implementation, and when the CNN-based skin disease classification is combined with the federated learning technique, it is a spectacular idea for classifying human skin disorders while maintaining data security.

The authors in [60] provide a semi-supervised federated learning strategy that builds communities and encourages its members to learn from one another so that they can generate more accurate pseudo-labels. This method uses peer learning and ensemble averaging from committee machines. They also suggest the peer anonymization (PA) method as a fundamental element. PA maintains performance without adding complexity while preserving privacy and lowering communication costs. An asynchronous weighted aggregation method with CNN for skin lesion prediction is proposed in [61], which asynchronously aggregates the received weights to lower the communication cost. Their suggested method optimizes communication rounds by dividing the CNN layers into shallow and deep layers, with the shallow layers being updated more frequently. The performance of CNN in federated learning settings for skin cancer is determined in [62]. In Table 4, a summary of the above-mentioned FL algorithms is provided.

Table 4. Summary of skin cancer prediction using FL-based algorithms.

Method	**Dataset Used**	**Objective**	**Accomplishments**
FL-Ensemble-CNN [57]	ISIC-2019	Adaptiveness for the FL algorithm	Their technique was able to achieve 95% accuracy with stable conditions and 89% accuracy with complex data.
FL-MM [58]	Skin Cancer and Patient Record Datasets	Multimodal FL-based algorithm	Their algorithm provides better sensitivity (3.3% higher) as compared with traditional ML settings.
FL-Aug-CNN [59]	Customized Image Dataset	Classification for Skin lesions	Their proposed method provides higher precision and better accuracy when increasing the number of HSP clients.
Fed-Perl [60]	Five Public Skin Cancer Datasets	Semi-supervised learning mechanisms in the FL environment	Their method achieves better classification accuracy as compared with state-of-the-art algorithms.
Async-FL-CNN [61]	ISIC-2019	Reduction of communication costs	They were able to achieve better communication efficiency with higher prediction accuracy.

6. Research Challenges Using FL for Skin Cancer

FL is a recently developed method to overcome the privacy concerns in traditional machine learning approaches for the healthcare system. Researchers have addressed skin cancer prediction issues using privacy-aware FL algorithms [57–62]. However, due to the evolving and complex nature of the dermoscopy image datasets available for skin cancer and the impact of skin disease on humans, an effective FL algorithm and its technologies are required, which could result in interesting research domains as follows:

- **Communication-Efficient FL Strategies:** The FL algorithms require communication among participants in the FL environment. As a result, FL relies on communication-efficient algorithms that deliver updated weights or the model changes repeatedly as part of the distributed training process.
- **Learning Rate for FL:** To correctly evaluate and interpret the features from dermoscopy pictures, the system must undergo rigorous training, which is a time-consuming procedure that needs exceptionally strong hardware in FL-based skin cancer detection approaches.
- **Effect of heterogeneity in FL:** The devices that make up a FL network may have quite different computing capacities. It is necessary to create FL techniques that can cope with the number of dropped devices in the network, low participation expectations, and diverse hardware.
- **Optimization-Aware FL:** The automated identification of skin cancer involves several highly important phases, including preprocessing and lesion edge detection. It is possible to investigate different optimization strategies to improve the efficiency of automated skin cancer diagnosis systems.
- **Data imbalance with FL:** The real-world datasets that are utilised to diagnose skin cancer are quite imbalanced. Each form of skin lesion has a substantially variable quantity of dermoscopy images in the imbalanced datasets.
- **Improved Privacy with FL:** The state-of-the-art FL technique may likewise pose privacy issues in a situation where there are dishonest clients and servers. As a result, additional debate is required on how to achieve a more trustworthy FL by eliminating all potential dangers.

7. Conclusions

Traditional machine learning and artificial intelligence-based healthcare systems face limitations due to global privacy laws, making them ineffective. As a solution, federated learning has emerged to develop privacy-aware healthcare systems. Skin cancer, a serious type of cancer, can be highly treatable when detected early. This paper provides a review of traditional machine learning algorithms for skin cancer prediction and discusses the effectiveness of federated learning-based algorithms. The application of federated learning techniques offers improved privacy-aware solutions for healthcare systems governed by international privacy laws. However, implementing federated learning algorithms for skin cancer prediction poses challenges such as patient data imbalance, distribution of dermoscopy images among client nodes, model convergence rate, communication size utilization, prediction accuracy, model loss during training, and model complexity. Further research and investigation are necessary to explore the adoption of federated learning in skin cancer prediction due to its recent development and potential benefits.

Author Contributions: Conceptualization, M.M.Y., U.F.K. and M.A.K.; methodology, M.M.Y., M.A. (Musleh Alsulami) and D.A.; software, M.A. (Mohammed AlKhathami), A.K.J.S. and M.M.Y.; validation, M.A.K., D.A., U.F.K. and M.A. (Musleh Alsulami); formal analysis, M.M.Y. and A.K.J.S.; investigation, A.K.J.S. and M.A.K.; resources, M.M.Y. and M.A.K.; data curation, M.M.Y., U.F.K. and M.A. (Musleh Alsulami); writing—original draft preparation, M.M.Y., M.A. (Mohammed AlKhathami) and A.K.J.S.; writing—review and editing, M.M.Y., M.A.K., M.A. (Musleh Alsulami) and D.A.; visualization, M.M.Y. and M.A.K.; supervision, M.A. (Musleh Alsulami); project administration, M.A. (Musleh Alsulami), A.K.J.S., D.A. and M.A.K.; funding acquisition, M.A. (Musleh Alsulami). All authors have read and agreed to the published version of the manuscript.

Funding: Deanship for Research and Innovation, Ministry of Education in Saudi Arabia, for funding this research work through the project number: IFP22UQU4290525DSR227.

Data Availability Statement: Any questions concerning the study in this publication are welcome and can be directed to the lead author (Muhammad Amir Khan) upon request.

Acknowledgments: The authors extend their appreciation to the Research and Innovation, Ministry of Education in Saudi Arabia, for funding this research work through the project number: IFP22UQU4290525DSR227.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Kalwa, U.; Legner, C.; Kong, T.; Pandey, S. Skin Cancer Diagnostics with an All-Inclusive Smartphone Application. *Symmetry* **2019**, *11*, 790. [CrossRef]
2. Pacheco, A.G.; Krohling, R.A. The impact of patient clinical information on automated skin cancer detection. *Comput. Biol. Med.* **2020**, *116*, 103545. [CrossRef]
3. Guo, Y.; Ashour, A.S.; Smarandache, F. A Novel Skin Lesion Detection Approach Using Neutrosophic Clustering and Adaptive Region Growing in Dermoscopy Images. *Symmetry* **2018**, *10*, 119. [CrossRef]
4. Voigt, P.; von dem Bussche, A.; Voigt, P.; von dem Bussche, A. Scope of application of the GDPR. In *The EU General Data Protection Regulation*; Springer: Cham, Switzerland, 2017; pp. 9–30.
5. Wagner, J. China's Cybersecurity Law: What you need to know. The Diplomat. June 2017. Available online: https://thediplomat.com/2017/06/chinas-cybersecurity-law-what-you-need-to-know/ (accessed on 18 January 2023).
6. de la Torre, L. A guide to the California Consumer Privacy Act of 2018. 2018. Available online: https://doi.org/10.2139/ssrn.3275571 (accessed on 18 January 2023).
7. McMahan, B.; Moore, E.; Ramage, D.; Hampson, S.; y Arcas, B.A. Communication-Efficient Learning of Deep Networks from Decentralized Data. In Proceedings of the 20th International Conference on Artificial Intelligence and Statistics, Fort Lauderdale, FL, USA, 9–11 May 2017; pp. 1273–1282.
8. McMahan, B.; Ramage, D. Federated Learning: Collaborative Machine Learning without Centralized Training Data. *Google AI Blog* **2017**, *3*. Available online: https://ai.googleblog.com/2017/04/federated-learning-collaborative.html (accessed on 21 January 2023).
9. Yaqoob, M.M.; Nazir, M.; Yousafzai, A.; Khan, M.A.; Shaikh, A.A.; Algarni, A.D.; Elmannai, H. Modified Artificial Bee Colony Based Feature Optimized Federated Learning for Heart Disease Diagnosis in Healthcare. *Appl. Sci.* **2022**, *12*, 12080. [CrossRef]
10. Wang, H.; Yurochkin, M.; Sun, Y.; Papailiopoulos, D.; Khazaeni, Y. Federated learning with matched averaging. *arXiv* **2020**, arXiv:2002.06440.
11. Nguyen, H.T.; Sehwag, V.; Hosseinalipour, S.; Brinton, C.G.; Chiang, M.; Poor, H.V. Fast-Convergent Federated Learning. *IEEE J. Sel. Areas Commun.* **2021**, *39*, 201–218. [CrossRef]
12. Ma, Z.; Zhao, M.; Cai, X.; Jia, Z. Fast-convergent federated learning with class-weighted aggregation. *J. Syst. Archit.* **2021**, *117*, 102125. [CrossRef]
13. Cheng, W.; Ou, W.; Yin, X.; Yan, W.; Liu, D.; Liu, C. A Privacy-Protection Model for Patients. *Secur. Commun. Netw.* **2020**, *2020*, 6647562. [CrossRef]
14. Yang, Z.; Chen, M.; Saad, W.; Hong, C.S.; Shikh-Bahaei, M. Energy Efficient Federated Learning Over Wireless Communication Networks. *IEEE Trans. Wirel. Commun.* **2021**, *20*, 1935–1949. [CrossRef]
15. Nguyen, V.D.; Sharma, S.K.; Vu, T.X.; Chatzinotas, S.; Ottersten, B. Efficient Federated Learning Algorithm for Resource Allocation in Wireless IoT Networks. *IEEE Internet Things J.* **2021**, *8*, 3394–3409. [CrossRef]
16. Fang, L.; Liu, X.; Su, X.; Ye, J.; Dobson, S.; Hui, P.; Tarkoma, S. Bayesian Inference Federated Learning for Heart Rate Prediction. In Proceedings of the International Conference on Wireless Mobile Communication and Healthcare, Virtual Event, 19 November 2020; Springer: Berlin/Heidelberg, Germany, 2020; pp. 116–130.
17. Codella, N.C.; Gutman, D.; Celebi, M.E.; Helba, B.; Marchetti, M.A.; Dusza, S.W.; Kalloo, A.; Liopyris, K.; Mishra, N.; Kittler, H.; et al. Skin Lesion Analysis toward Melanoma Detection: A Challenge at the International Symposium on Biomedical Imaging (ISBI) 2016, hosted by the International Skin Imaging Collaboration (ISIC). *arXiv* **2016**, arXiv:1605.01397.
18. Codella, N.C.F.; Gutman, D.; Celebi, M.E.; Helba, B.; Marchetti, M.A.; Dusza, S.W.; Kalloo, A.; Liopyris, K.; Mishra, N.; Kittler, H.; et al. Skin lesion analysis toward melanoma detection: A challenge at the 2017 International symposium on biomedical imaging (ISBI), hosted by the international skin imaging collaboration (ISIC). In Proceedings of the 2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018), Washington, DC, USA, 4–7 April 2018; pp. 168–172. [CrossRef]
19. Wen, H.; Xu, R.; Zhang, T. ISIC 2018-A method for lesion segmentation. *arXiv* **2018**, arXiv:1807.07391.
20. Larxel. Skin Lesion Images for Melanoma Classification. 2019. Available online: https://www.kaggle.com/datasets/andrewmvd/isic-2019 (accessed on 12 February 2023).
21. Rotemberg, V.; Kurtansky, N.; Betz-Stablein, B.; Caffery, L.; Chousakos, E.; Codella, N.; Combalia, M.; Dusza, S.; Guitera, P.; Gutman, D.; et al. A patient-centric dataset of images and metadata for identifying melanomas using clinical context. *Sci. Data* **2021**, *8*, 34. [CrossRef]
22. Tschandl, P.; Rosendahl, C.; Kittler, H. The HAM10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions. *Sci. Data* **2018**, *5*, 180161. [CrossRef]

23. Combalia, M.; Codella, N.C.F.; Rotemberg, V.; Helba, B.; Vilaplana, V.; Reiter, O.; Carrera, C.; Barreiro, A.; Halpern, A.C.; Puig, S.; et al. BCN20000: Dermoscopic Lesions in the Wild. arXiv 190802288 Cs Eess. 30 August 2019. Available online: http://arxiv.org/abs/1908.02288 (accessed on 20 December 2022).
24. DERMOFIT. Available online: https://homepages.inf.ed.ac.uk/rbf/DERMOFIT/ (accessed on 22 December 2022).
25. PH2-A Dermoscopic Image Database for Research and Benchmarking. Available online: https://ieeexplore.ieee.org/abstract/document/6610779/ (accessed on 22 December 2022).
26. de Faria, S.M.M.; Henrique, M.; Filipe, J.N.; Pereira, P.M.M.; Tavora, L.M.N.; Assuncao, P.A.A.; Santos, M.O.; Fonseca-Pinto, R.; Santiago, F.; Dominguez, V. Light field image dataset of skin lesions. In Proceedings of the 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Berlin, Germany, 23–27 July 2019; pp. 3905–3908. [CrossRef]
27. SynthDerm. Available online: https://affect.media.mit.edu/dissect/synthderm/ (accessed on 22 December 2022).
28. Yan, K.; Wang, X.; Lu, L.; Summers, R.M. DeepLesion: Automated mining of large-scale lesionannotations and universal lesion detection with deep learning. *J. Med. Imaging* **2018**, *5*, 036501. [CrossRef]
29. Murugan, A.; Nair, S.A.H.; Preethi, A.A.P.; Kumar, K.P.S. Diagnosis of skin cancer using machine learning techniques. *Microprocess. Microsyst.* **2021**, *81*, 103727. [CrossRef]
30. Monika, M.K.; Vignesh, N.A.; Kumari, C.U.; Kumar, M.; Lydia, E.L. Skin cancer detection and classification using machine learning. *Mater. Today Proc.* **2020**, *33*, 4266–4270. [CrossRef]
31. Monika, M.K.; Vignesh, N.A.; Kumari, C.U.; Kumar, M.; Lydia, E.L. Artificial intelligence and machine learning algorithms for early detection of skin cancer in community and primary care settings: A systematic review. *Lancet Digit. Health* **2022**, *4*, 466–476.
32. Dai, X.; Spasić, I.; Meyer, B.; Chapman, S.; Andres, F. Machine learning on mobile: An on-device inference app for skin cancer detection. In Proceedings of the 2019 Fourth International Conference on Fog and Mobile Edge Computing (FMEC), Rome, Italy, 10–13 June 2019; pp. 301–305.
33. Nyemeesha, V.; Ismail, B.M. A Systematic Study and Approach On Detection Of Classification Of Skin Cancer Using Back Propagated Artificial Neural Networks. *Turk. J. Comput. Math. Educ.* **2021**, *12*, 1737–1748.
34. Daghrir, J.; Tlig, L.; Bouchouicha, M.; Sayadi, M. Melanoma skin cancer detection using deep learning and classical machine learning techniques: A hybrid approach. In Proceedings of the 2020 5th International Conference on Advanced Technologies for Signal and Image Processing (ATSIP), Sousse, Tunisia, 2–5 September 2020; pp. 1–5.
35. Ali, M.S.; Miah, M.S.; Haque, J.; Rahman, M.M.; Islam, M.K. An enhanced technique of skin cancer classification using deep convolutional neural network with transfer learning models. *Mach. Learn. Appl.* **2021**, *5*, 100036. [CrossRef]
36. Nauta, M.; Walsh, R.; Dubowski, A.; Seifert, C. Uncovering and Correcting Shortcut Learning in Machine Learning Models for Skin Cancer Diagnosis. *Diagnostics* **2021**, *12*, 40. [CrossRef] [PubMed]
37. Magalhaes, C.; Tavares, J.M.R.; Mendes, J.; Vardasca, R. Comparison of machine learning strategies for infrared thermography of skin cancer. *Biomed. Signal Process. Control* **2021**, *69*, 102872. [CrossRef]
38. Putra, T.A.; Rufaida, S.I.; Leu, J.-S. Enhanced Skin Condition Prediction through Machine Learning Using Dynamic Training and Testing Augmentation. *IEEE Access* **2020**, *8*, 40536–40546. [CrossRef]
39. Ashraf, R.; Afzal, S.; Rehman, A.U.; Gul, S.; Baber, J.; Bakhtyar, M.; Mehmood, I.; Song, O.-Y.; Maqsood, M. Region-of-Interest Based Transfer Learning Assisted Framework for Skin Cancer Detection. *IEEE Access* **2020**, *8*, 147858–147871. [CrossRef]
40. Hekler, A.; Utikal, J.S.; Enk, A.H.; Hauschild, A.; Weichenthal, M.; Maron, R.C.; Berking, C.; Haferkamp, S.; Klode, J.; Schadendorf, D.; et al. Superior skin cancer classification by the combination of human and artificial intelligence. *Eur. J. Cancer* **2019**, *120*, 114–121. [CrossRef]
41. Das, K.; Cockerell, C.J.; Patil, A.; Pietkiewicz, P.; Giulini, M.; Grabbe, S.; Goldust, M. Machine Learning and Its Application in Skin Cancer. *Int. J. Environ. Res. Public Health* **2021**, *18*, 13409. [CrossRef] [PubMed]
42. Anand, V.; Gupta, S.; Altameem, A.; Nayak, S.R.; Poonia, R.C.; Saudagar, A.K.J. An Enhanced Transfer Learning Based Classification for Diagnosis of Skin Cancer. *Diagnostics* **2022**, *12*, 1628. [CrossRef]
43. Dey, N.; Rajinikanth, V.; Ashour, A.S.; Tavares, J.M.R.S. Social Group Optimization Supported Segmentation and Evaluation of Skin Melanoma Images. *Symmetry* **2018**, *10*, 51. [CrossRef]
44. Rout, R.; Parida, P.; Alotaibi, Y.; Alghamdi, S.; Khalaf, O.I. Skin Lesion Extraction Using Multiscale Morphological Local Variance Reconstruction Based Watershed Transform and Fast Fuzzy C-Means Clustering. *Symmetry* **2021**, *13*, 2085. [CrossRef]
45. Ali, M.D.; Saleem, A.; Elahi, H.; Khan, M.A.; Khan, M.I.; Yaqoob, M.M.; Farooq Khattak, U.; Al-Rasheed, A. Breast Cancer Classification through Meta-Learning Ensemble Technique Using Convolution Neural Networks. *Diagnostics* **2023**, *13*, 2242. [CrossRef]
46. Ashour, A.S.; Du, C.; Guo, Y.; Hawas, A.R.; Lai, Y.; Smarandache, F. A Novel Neutrosophic Subsets Definition for Dermoscopic Image Segmentation. *IEEE Access* **2019**, *7*, 151047–151053. [CrossRef]
47. Malik, S.; Akram, T.; Awais, M.; Khan, M.A.; Hadjouni, M.; Elmannai, H.; Alasiry, A.; Marzougui, M.; Tariq, U. An Improved Skin Lesion Boundary Estimation for Enhanced-Intensity Images Using Hybrid Metaheuristics. *Diagnostics* **2023**, *13*, 1285. [CrossRef]
48. Ajmal, M.; Khan, M.A.; Akram, T.; Alqahtani, A.; Alhaisoni, M.; Armghan, A.; Althubiti, S.A.; Alenezi, F. BF^{2}SkNet: Best deep learning features fusion-assisted framework for multiclass skin lesion classification. *Neural Comput. Appl.* **2022**, 1–17. [CrossRef]
49. Khan, M.A.; Sharif, M.I.; Raza, M.; Anjum, A.; Saba, T.; Shad, S.A. Skin lesion segmentation and classification: A unified framework of deep neural network features fusion and selection. *Expert Syst.* **2022**, *39*, e12497. [CrossRef]

50. Afza, F.; Sharif, M.; Khan, M.A.; Tariq, U.; Yong, H.-S.; Cha, J. Multiclass Skin Lesion Classification Using Hybrid Deep Features Selection and Extreme Learning Machine. *Sensors* **2022**, *22*, 799. [CrossRef]
51. Balaha, H.M.; Hassan, A.E. Skin cancer diagnosis based on deep transfer learning and sparrow search algorithm. *Neural Comput. Appl.* **2023**, *35*, 815–853. [CrossRef]
52. Babar, M.; Khan, M.S.; Din, A.; Ali, F.; Habib, U.; Kwak, K.S. Intelligent Computation Offloading for IoT Applications in Scalable Edge Computing Using Artificial Bee Colony Optimization. *Complexity* **2021**, *2021*, 5563531. [CrossRef]
53. Munagala, N.K.; Langoju, L.R.R.; Rani, A.D.; Reddy, D.R.K. A smart IoT-enabled heart disease monitoring system using meta-heuristic-based Fuzzy-LSTM model. *Biocybern. Biomed. Eng.* **2022**, *42*, 1183–1204. [CrossRef]
54. Ma, N.; Men, Y.; Men, C.; Li, X. Accurate Dense Stereo Matching Based on Image Segmentation Using an Adaptive Multi-Cost Approach. *Symmetry* **2016**, *8*, 159. [CrossRef]
55. Khurshid, W.; Laiha Mat Kiah, M.; Khan, I.A.; Salleh, R.; Chronopoulos, A.T.; Madani, S.A. Comparative study of congestion notification techniques for hop-by-hop-based flow control in data centre Ethernet. *IET Netw.* **2018**, *7*, 248–257. [CrossRef]
56. Obayya, M.; Alhebri, A.; Maashi, M.; Salama, A.S.; Hilal, A.M.; Alsaid, M.I.; Osman, A.E.; Alneil, A.A. Henry Gas Solubility Optimization Algorithm based Feature Extraction in Dermoscopic Images Analysis of Skin Cancer. *Cancers* **2023**, *15*, 2146. [CrossRef] [PubMed]
57. Hashmani, M.A.; Jameel, S.M.; Rizvi, S.S.H.; Shukla, S. An Adaptive Federated Machine Learning-Based Intelligent System for Skin Disease Detection: A Step toward an Intelligent Dermoscopy Device. *Appl. Sci.* **2021**, *11*, 2145. [CrossRef]
58. Agbley, B.L.Y.; Li, J.; Haq, A.U.; Bankas, E.K.; Ahmad, S.; Agyemang, I.O.; Kulevome, D.; Ndiaye, W.D.; Cobbinah, B.; Latipova, S. Multimodal Melanoma Detection with Federated Learning. In Proceedings of the 2021 18th International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP), Chengdu, China, 17–19 December 2021; pp. 238–244.
59. Hossen, M.N.; Panneerselvam, V.; Koundal, D.; Ahmed, K.; Bui, F.M.; Ibrahim, S.M. Federated Machine Learning for Detection of Skin Diseases and Enhancement of Internet of Medical Things (IoMT) Security. *IEEE J. Biomed. Health Inform.* **2023**, *27*, 835–841. [CrossRef] [PubMed]
60. Bdair, T.; Navab, N.; Albarqouni, S. FedPerl: Semi-supervised peer learning for skin lesion classification. In Proceedings of the Medical Image Computing and Computer Assisted Intervention—MICCAI 2021: 24th International Conference, Strasbourg, France, 27 September–1 October 2021; pp. 336–346, Part III.
61. Yaqoob, M.M.; Alsulami, M.; Khan, M.A.; Alsadie, D.; Saudagar, A.K.J.; AlKhathami, M. Federated Machine Learning for Skin Lesion Diagnosis: An Asynchronous and Weighted Approach. *Diagnostics* **2023**, *13*, 1964. [CrossRef] [PubMed]
62. Li, Y.; He, Y.; Fu, Y.; Shan, S. Privacy Preserved Federated Learning for Skin Cancer Diagnosis. In Proceedings of the 2023 IEEE 3rd International Conference on Power, Electronics and Computer Applications (ICPECA), Shenyang, China, 29–31 January 2023; pp. 27–33. [CrossRef]

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