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TOPICAL REVIEW

Terahertz Data Extraction and Analysis Based on Deep Learning Techniques for Emerging Applications

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ABSTRACT Following the recent progress in the development of Terahertz (THz) generation and detection, THz technology is being widely used to characterize test sample properties in various applications including nondestructive testing, security inspection and medical applications. In this paper, we have presented a broad review of the recent usage of artificial intelligence (AI) particularly, deep learning techniques in various THz sensing, imaging, and spectroscopic applications with emphasis on their implementation for medical imaging of cancerous cells. Initially, the fundamentals principles and techniques for THz generation and detection, imaging and spectroscopy are introduced. Subsequently, a brief overview of AI – machine learning and deep learning techniques is summarized, and their performance is compared. Further, the usage of deep learning algorithms in various THz applications is reported, with focus on metamaterials design and classification, detection, reconstruction, segmentation, parameter extraction and denoising tasks. Moreover, we also report the metrics used to evaluate the performance of deep learning models and finally, the existing research challenges in the application of deep learning in THz cancer imaging applications are identified and possible solutions are suggested through emerging trends. With the continuous increase of acquired THz data – sensing, spectral and imaging, artificial intelligence has emerged as a dominant paradigm for embedded data extraction, understanding, perception, decision making and analysis. Towards this end, the integration of state-of-the-art machine learning techniques such as deep learning with THz applications enable detailed computational and theoretical analysis for better validation and verification than modelling techniques that precede the era of machine learning. The study will facilitate the large-scale clinical applications of deep learning enabled THz imaging systems for the development of smart and connected next generation healthcare systems as well as provide a roadmap for future research direction.

INDEX TERMS Artificial intelligence, deep learning, terahertz technology.

I. INTRODUCTION

The Global Terahertz (THz) technology research and markets forecast report of 2022 projected the market rise sharply from USD 420 million in 2021 and reach USD 2,879 million by 2030 with compound annual growth rate (CAGR) of 23.8% from 2022 to 2030 [1]. The increasing investments are anticipated to steadily grow THz technology market in developing regions and countries due to the rising sectors including healthcare. To complement these resurgent trends, it is imperative to continually develop state-of-the-art THz sensing, imaging and spectroscopy systems by integrating them with advanced techniques such as deep learning. This is crucial in overcoming bottlenecks in practical applications thus, meeting the market demands and ensuring their efficient and wide-scale utilization in various real-time operational environments.

Being located within the 100GHz to 10THz frequency range, the THz wave-based technology has boosted rapid development and research on its exploration in diverse fields

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including quality and security inspection, astronomy, non-destructive testing (NDT), biomedical characterization and material estimation. The THz band is sandwiched between the microwave and infrared (IR) bands of the electromagnetic spectrum. Therefore, it is regarded as a transitional region in which optics meets electronics. The THz radiation is treated as a light beam in the optical domain whose light intensity can be measured and can be manipulated by lenses and mirrors. However, in the electronics domain, the THz radiation is considered an electrical wave with a measurable phase of the electrical field. Owing to its low photon energy of 4MeV at 1Hz, the THz radiation is nonionizing and can be used for noninvasive observations of biological tissues without posing significant harm. Also, many chemical and biological materials exhibit unique spectral fingerprinting in the THz spectrum for example, the vibrational modes of THz allow molecular structure and vibrational dynamics studies that arise from intermolecular and intramolecular interactions. Further, the THz radiation is strongly absorbed by water molecules which enable water dynamics observations and inspection of metallic components enabled through the capability of THz radiation to be reflected by metals and penetrate dielectric, amorphous and non-conducting materials [2].

The ongoing development of strong field, high energy THz generation and detection devices has led to the exploration of THz technology in various sensing, imaging, and spectroscopy applications through an anticipated integration with other technologies like robotics, artificial intelligence (AI) and internet-of-things (IoT) etc. As a result of the rapid THz technology evolution and their near future increased availability, the application of THz technology is expected to expand. The acquired THz data include 1-dimensional (1D) signal, 2-dimensional (2D) spatial domain images and temporal data. Therefore, it is required to appropriately analyze the acquired signal for embedded information extraction, which regardless of the objective becomes a potential AI application. Conventional AI techniques use a knowledge-based approach which is an analytical approach that uses mathematical representation of a problem and search for a possible solution under certain constraints. However, for most tasks, the problem is not clearly described by mathematical rules because the main tasks are not suited to specific step-by-step processes and often abstract. An advanced machine learning i.e., the deep learning techniques are able to automatically learn from training data, reason and adapt without being programmed explicitly, thus it is widely used in THz based tasks [3].

The deep learning techniques have in recent years been widely used to enhance the performance of THz technology through providing support for data processing, reducing the number of variables and higher prediction accuracy and efficiency with reduced human intervention. The application of machine learning in THz technology has been commonly realized in the following tasks. The reconstruction and denoising tasks which are intended for image and spectrum preprocessing to remove unwanted or irrelevant information and reduce number of variables from spectral and image parameters thus increasing the data analysis efficiency [4]. The machine learning methods are also used for multivariate quantitative and qualitative analysis of data for highly precise classification and recognition of samples [2].

However, due to the unavailability of sufficient training datasets, the deep learning technique has been scarcely investigated in THz cancer imaging datasets. Instead, a couple of studies have explored the application of deep learning approach for THz datasets in NDT, security inspection, THz metamaterial design, agriculture and biological tissue assessment applications etc. as shall be reported in this work. The exploration of deep learning approach in such THz applications and the identification of existing challenges will contribute to the ongoing research and facilitate the large-scale medical applications of deep learning enabled THz systems.

A. RELATED WORK

An in-depth review of machine learning and deep learning techniques for signal processing and classification for efficient THz communication and sensing was presented in [2]. The article promoted the significance of THz frequency domain spectroscopy (FDS) and THz time domain spectroscopy (THz TDS) in future reconfigurable. THz systems. The THz channels effects on sensing performance have been numerically validated using simulations based on realistic data to pave the way for future research scope. An overview of the signal processing like Savitzky Golay filtering, standard normal variate and min-max normalization as well as techniques for feature extraction for instance Principal component analysis (PCA) etc. was presented. Further, the classification techniques based on ML like support vector machine (SVM), k-nearest neighbors (kNN), the Naïve Bayes and discriminant analysis are presented for qualitative and quantitative analysis in joint THz communication and sensing. The approaches for alleviating existing challenges towards the next generation, robust, adaptive, and fast THz communication and sensing platforms have also been provided. The sensing capabilities of deep learning techniques in the THz band was also explored, with the complexity and performance trade-offs of the techniques in sensing and joint communications studied [2].

The challenges associated with machine learning methods combined with THz systems such as low accuracy, high water absorption, high cost and low spatial resolution have also been addressed for improved robustness and generality of models for THz data analysis. The application of ML techniques to analyze acquired THz signals so as to extract embedded information was reviewed by Park and Son [3]. The basic machine learning techniques and statistical performance evaluation methods were described, they examined THz imaging and spectroscopy applications based on ML techniques for various tasks like disease diagnosis, estimation of disease level, materials identification, and component analysis.

A comprehensive analysis of biomedical image and the classification of images based on dynamic contrast enhanced magnetic resonance imaging (DCE-MRI) and its complementary, the THz pulse imaging (TPI) was reported by Yin et al. [5] with the aim to develop a unified multi-channel framework that would explore synergies between the two modalities for disease proliferation inference. They highlighted the commonalities in the data structures of both imaging modalities so as to enable development of a data fusion multi-channel framework for enabling software standardization. They discussed preprocessing and statistical signal processing algorithms for both modalities using PCA and the independent component analysis (ICA). They presented feature extraction and classification methods based on SVM, the extreme learning machine (ELM) and using deep learning methodologies that are applicable to both modalities. The potential contribution as a review in terms of interdisciplinary research, existing methodologies in the fields of biomedical engineering, nano-engineering and ML has been provided by Boulogeorgos et al. [6]. They presented the main challenges that can be solved by the use of ML techniques, for example in biomedical applications for development of therapies and detection of disease. The ML methodologies, their principles, building blocks and architectures were also reported. The advantages and disadvantages of each ML based technique were also highlighted.

The application of machine learning techniques such as SVM, kNN, Random forest and Naïve Bayes have been reported for THz TDS imaging analysis in the NDT, security and painting applications [7]. The review of artificial intelligence enabled THz wireless technologies to meet demands for next generation networks of high rate services have also been reported in [8], [9], and [10]. Additional review papers on Terahertz sensing have been reported in [11], [12], [13], and [14]. The application of conventional machine learning has been investigated in THz technology for example Support vector machine (SVM) [15], [16] k-nearest neighbors (KNN) [15], [17], the Random forest (RF) algorithm [15] and artificial neural networks (ANN) [17]. The use of deep learning and various ML algorithms have been widely explored in other well established biomedical imaging modalities and applications and some of them include. The identification of endometriosis presence from MRI images as well as the severity determination was surveyed by [18] which would create personalized treatment opportunities. The application of the ML and deep learning techniques for example SVM and use of the convolutional neural networks algorithm (CNN) in the field of biomedical imaging using various modalities for classification have been reported to have achieved great results [19], [20], [21], [22], [23], [24]. Tchapga et al. [25], reported the application of classification algorithms for biomedical imaging analysis. The categorization of medical image datasets using ML classification algorithms before diagnosis was also reported in [26], [27], [28], [29], [30], [31], and [32] and various efforts to improve biomedical image classifications investigated in [33], [34], [35], [36], [37], [38], [39], and [40]. A survey of disease diagnosis using ML classification techniques on medical images from various modalities where SVM and ANN was found to give the highest accuracy, sensitivity and specificity in [35] and in [36] SVM and ANN were reported to contribute up to 42% and 31% respectively of the most used algorithms. The application of ML based algorithms for detection of various cancer and classification of images acquired using various imaging modalities (mostly the conventional modalities) were reported in several other studies like [25], [34], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], and [62].

B. MOTIVATION

With the continuous increase (in terms of volumes, variety and velocity) of imaging data that comes along with the advancements in the imaging technology leading to the emergence of new imaging modalities like THz imaging etc., the use of deep learning and big data technologies is a necessity. Training intelligent models are required to aid the detection, classification, prediction, and localization of various targets. The commonly used machine learning based modeling tools use shallow structures. This poses challenges in gathering in-depth feature information from THz spectral and image data, hence limiting the prediction robustness to a task specific application with limited accuracy. It is therefore recommendable that deep learning methods are applied in THz technology for improved robustness and accuracy of prediction models.

C. CONTRIBUTION

The application of deep learning in THz imaging applications has not yet been fully explored. The existing review papers mostly focused on ML in the THz imaging and sensing applications. Other related reviews focused on reporting the progress of task specific ML techniques applications in THz and the THz developmental progress in THz studies. In this paper, we give a broad review of the recent applications of artificial intelligence, particularly deep learning techniques in THz sensing, imaging and spectroscopy applications towards their implementation in medical imaging for cancer. More specifically.

- The fundamentals, principles and techniques for THz generation and detection, imaging and spectroscopy are introduced.
- A brief overview of AI – machine learning and deep learning techniques is summarized, and their performance compared.
- The application of deep learning algorithms in various THz applications is reported, with more focus on metamaterials design and classification, detection, reconstruction, segmentation, parameter extraction and denoising tasks.
- We report the metrics used to evaluate the performance of deep learning models.

- The existing research challenges are identified, and possible solutions suggested. This will facilitate the large-scale clinical applications of deep learning enabled THz imaging systems for smart and connected next generation healthcare and provide a roadmap for future research.

D. ORGANIZATION

This review paper is made up of seven sections. The remainder of the work is organized in the following sections as follows. The second section gave an overview of THz technology and in the third section we report an overview of AI, summarizing the ML and deep learning techniques. The fourth section presented the application of deep learning techniques for various tasks such as classification, detection, identification etc. in the various THz sensing, imaging, and spectroscopy applications. The metrics for evaluation of deep learning model performance are reported in the fifth section. In the sixth section we discuss the existing challenges inhibiting the application of deep learning in THz biomedical applications, particularly cancer imaging. The suggested solutions are envisaged to pave the way and provide scope for future research. The summary of the paper is given in the seventh section.

II. OVERVIEW OF THz TECHNOLOGY

Based on the THz radiation generated, the two broad categories of THz radiation generation schemes are the continuous wave (CW) THz and the pulsed wave THz. The most commonly used THz system for biological samples is the THz time-domain spectroscopy (THz-TDS) system also called THz pulsed spectroscopy (TPS) that is based on femtosecond lasers and enables direct measurement of absorption coefficient and refractive index and hence the sample's complex permittivity in a single scan and broad frequency range [190], [205], [206].

The THz pulsed imaging (TPI) system shown in Fig. 1 is an extension of the THz TDS and they can be interchanged by switching the scanning mechanism. This can be achieved through movement (lateral translation) of the sample with the illumination beam stationery so as to perform point to point collection (raster scanning) of 2-dimensional information. A typical THz system is made up of a source, detector and optical components such as mirrors, lenses, polarizers and waveguides. In spectroscopy, the beam is moved using stages or piezoelectric rotators and/or galvo mirrors. For imaging, the THz beam illuminates the surface of the object, sampled by discrete grid and continuously scanned or pixel by pixel scanned in raster mode. The acquired information is obtained from the data acquisition card (DAQ), quantized to bits for further image processing [63].

The TPI uses a coherent detection method in which the THz signal's amplitude and phase values are measured, enabling refractive index, absorption coefficient parameters to be obtained. In TPI systems there are several techniques used for the detection and generation of THz radiation characterized by output of broadband frequencies (ranging tens - hundreds GHz to several THz). The mostly used sources for generation of pulsed THz radiation are based on optical rectification (OR) using nonlinear optical crystals (NLO), biased photoconductive antennas (PCAs), carrier tunneling and plasma in air. Most of the commonly used approaches are based on PCA and OR where infrared (IR) femtosecond lasers which emit in near infrared (NIR) are used. In PCA, the principle of operation is such that a beam of pulsed laser illuminates a PCA gap composed of thin semiconductor film of high resistance with two contact pads of electrical property. When the bias voltage and laser beam are applied, there is in turn generation of a photocurrent and free carriers are accelerated by the static bias field thereby producing broadband THz frequency to the free space [79], [93]. In OR, NLO centrosymmetric crystals are used to generate THz broadband from 0.1THz to more than 40THz. The NLO based crystals include organic NLO, 4-N, N-dimethylamino-4'-N'-methyl-stilbazolium tosylate (DAST) and 4-N, N-dimethylamino -4'-N'-methyl-stilbazolium 2,4,6-trimethylbenzenesulfonate (DSTMS). The principle of OR based sources is that intense beams of NIR laser are propagated through crystals, nonlinear effects of second order occur thereby low frequency of DC polarization is developed leading to an electromagnetic single cycle pulse radiation with broad frequency spectrum (from 0Hz to a particular maximum value). Alternatively, charges acceleration can lead to radiation of electromagnetic waves, and when certain conditions are reached, the produced electromagnetic waves lie in THz range. Acceleration of electrons can be achieved in vacuum, air or semiconductors by using application of bias voltage over the gap, or by laser beam's second harmonic and fundamental frequencies nonlinear four wave mixing in various gases or in air or using an intense pulse of laser. Another technique for THz pulsed radiation generation is surge whereby when bias voltage is applied on the semiconductor quantum wells (QWs), THz radiation is produced through mechanism of polarized electron hole pairs production [63]. THz TDS and THz CW

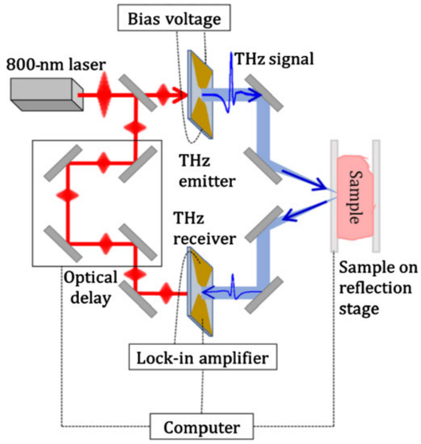

FIGURE 1. THz pulsed spectroscopy system.

techniques have been used for cancer and healthy tissues and can be implemented in reflection, transmission and attenuated total reflection configurations. Other THz techniques including THz computed tomography and multi-pixel camera-based imaging etc. have also been researched [64].

The THz sensing, imaging and spectroscopy has been widely explored in various applications such as NDT, security inspection, material characterization and wireless communication networks [65]. More recently, the application of THz technology in biomedical applications is gaining momentum.

In Table 1, some studies where THz technology for imaging and spectroscopy have been investigated for biomedical and cancer applications are presented.

III. ARTIFICIAL INTELLIGENCE OVERVIEW

ML is a subset of AI whose algorithms' performance improve over time as they are exposed to more data. In this section, the fundamentals of AI algorithms in THz technology applications are presented.

As shown in Fig. 2, the transfer learning (TL) and deep learning (DL) are a subclass of ML, and they are made up of neural networks with multiple layers. The ML approaches mimic the neural system of human, and the ML methodologies are categorized as: supervised learning and unsupervised learning, whereas AI uses knowledge-based approach. The most common methodology is supervised learning and in these techniques, a particular amount of labelled data is required for training [3], [76]. A function is created which maps input data onto output labels which rely on initial training in other words, a mapping function $g(x)$ is returned which maximizes $g(x_n, y_n)$ a scoring function for each $n \in [1, N]$ where x_n is the input's nth sample, y_n a label of x_n and N the training set size. The main tasks involved in the supervised learning applied for THz imaging are classification & regression, over fitting & generalization and feature extraction & reduction [3]. In an unsupervised learning, the hidden structure or features of data are explored without training. In more detail, unsupervised learning is also known as knowledge discovery, which is capable of determining hidden patterns using unlabeled data and without prediction datasets by clustering. Unsupervised learning is useful in applications where labeling is not relevant or is an expensive and its importance is being more realized in deep learning where there is need for big datasets, but it is difficult to get large and labelled datasets as well as in exploratory data analysis phase to discover latent patterns or to group data.

The AI particularly, machine learning and deep learning has been proving to significantly improve performance in processing medical images, with great potential to provide clinical decision support through the development of computer aided diagnostic (CAD) systems and for therapy development. Similarly, in the THz imaging domain, the application of ML techniques has been realized for localization of tumor from images through classification, detection and segmentation tasks etc. Prior research has mostly leveraged machine learning models that rely on statistical inference to classify THz image tissue regions and image segmentation with detection and recognition tasks as shown in Table 2.

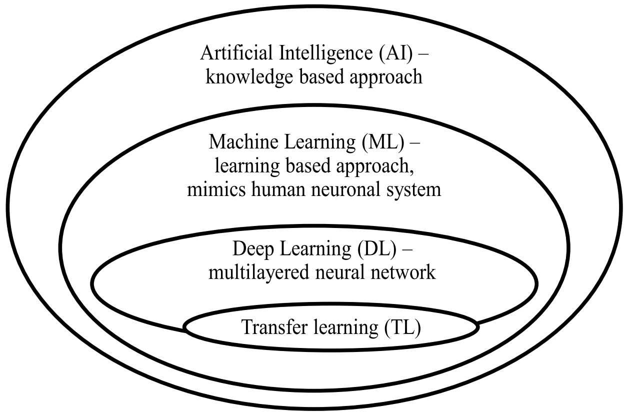

FIGURE 2. Subsets of Artificial intelligence for biomedical imaging.

As shown in Table 2, machine learning has been employed in various THz technology applications including cancer applications for signal preprocessing, feature extraction, segmentation, and classification tasks etc. Some of the machine learning techniques that have been employed in different THz imaging tasks include Support vector machines (SVM), Principal component analysis (PCA), k-means clustering, k nearest neighbors (kNN), Bayesian learning, Random Forest, Decision trees, Ensemble learning and Adaptive boosting etc. [3] [84]. However, these conventional machine learning models rely on statistical inference and the quality of classification in such techniques depend on the effectiveness of the preprocessing, feature extraction and segmentation operations for dimensionality reduction.

As a result of rapid developments in algorithmic improvements, increased quality datasets and computational power, deep learning neural networks have recently made significant advancements in the field of medical imaging with elimination of the need to manually extract features [85]. The CNN have recently shown to receive more attention in various image classification, denoising, identification tasks, as well as promising to provide an improved approach for THz image qualities since rapid THz imaging techniques usually suffer poor image reconstruction quality [86].

A. FUNDAMENTALS OF DEEP LEARNING

Recently, deep learning based on neural networks has shown to provide improved performance compared to the conventional machine learning models through automatic feature learning and back propagation in image segmentation, recognition and detection tasks [84]. Deep learning architectures are broadly categorized as supervised, unsupervised and reinforcement learning techniques. Some of the common deep learning techniques include the convolutional neural network (CNN), Recursive neural network (RvNN) and Recurrent neural networks (RNN).

TABLE 1. Biomedical applications of THz technology.

Ref.	Technique	Approach	Results	Limitations
[66]	Terahertz imaging	• The progress of THz cancer imaging for epithelial cancers like colon cancer and skin cancer was reported. • They proposed the possibility of integrating THz imaging systems with robotics (Terabotics) for real time THz cancer imaging. • Development of fast, compact probes.	• The potential of THz imaging technology to perform real time imaging was reported.	• Very high initial cost of THz equipment.
[67]	THz technology	• Reviewed biomedical applications of THz waves, summarizing their merits and demerits. • A model for biomarker determination, removal of interference and removal of individual differences.	• THz significant contribution to accurate, early and rapid disease detection.	• Lack of standardized models for accurate diagnosis
[68]	THz imaging and spectroscopy	• Application of THz imaging and spectroscopy for analysis and characterization of cancer and DNA. • Quantification through chemo metrics based on machine learning algorithms like SVM, PCA were reported.	• The potential of THz imaging and spectroscopy coupled with chemo metrics: • to improve diagnosis accuracy, • Bio molecular spectral identification in mixture systems.	• THz is yet to be developed to a medical tool capable of tissue information extraction.
[69]	THz technology	• Skin cancer detection and modulation/treatment was reported. • Recent THz achievements in skin diagnosis applications. • The improvement methods of THz imaging through contrast enhancement techniques were mentioned.	• High potential of THz imaging and spectroscopy for skin melanoma and non-melanoma diagnosis	• Small penetration depth of THz, • Spatial resolution measured by diffraction limit prevents single cell detection. • Expensive THz equipment
[70]	THz pulse detection system	• The detection of skin, colon and breast cancer was numerically analyzed. • Used semiconductor meta-material as a biosensor.	• Ability of THz pulse detection to differentiate between cancerous and normal tissue.	• The specificity and sensitivity of the used technique is to be further determined.
[71]	THz spectroscopy	• The potential of THz spectroscopy in molecular detection, environmental monitoring, and food industry. • THz significance in public health and disease control was described.	• Great potential of THz technology for future innovation, • Viability for development of emergency solutions for example in pandemics.	• Challenges related to development and establishment of THz technology hinder the progress of technology development.
[72]	THz spectroscopy technology	• THz spectroscopy for cancer cell characterization, blood cell detection, tissue discrimination and bacterial identification. • Effects of THz radiation on biological tissue	• THz technology is step by step being developed to become a clinical tool.	• Low detection sensitivity and specificity of the technology, • High THz absorption of water.
[73]	Spectral imaging technique in THz range	• The Physics, implementation issues and image analysis techniques required in THz.	• They discussed the suitability of THz spectral imaging technique in different applications	• Spectral noise, limited customizability and portability, long image acquisition times.
[74]	THz imaging and spectroscopy	• Biological tissue dielectric properties, • THz dielectric permittivity model of water which yields modes for damped resonant molecules and relaxation analysis. • Review of THz technology and its application in malignancies detection	• Potential use of hyperosmotic agents that are capable of cancer detection.	• THz limitation to deliver THz waves to internal and hard to access organs, limited penetrability.
[75]	THz imaging and spectroscopy	• THz technology diagnostic applications • Resolution enhancement and automated diagnosis techniques including through machine learning.	• The limitations of THz application in biophotonics were identified and the solutions proposed.	• Limited by low resolution and beam penetration depth due to high THz absorption of water.

The most commonly employed and famous deep learning network is the CNN which have been extensively used in various range of field applications [87], [88], [89]. The main salient property of CNN is its ability to automatically learn relevant image features without human supervision. The architecture of CNNs is shown in Fig. 3 and it mimics the activity of human and animal neurons. The CNN layers can be summarized as input layer, convolution layer, pooling layer, fully connected (fc) layer and output layer. A 3-D convolution of say $3 \times 3 \times 3$ is applied to an input image so as to compute the output image with characteristic representations of the input image. When different convolution filters are applied,

TABLE 2. Applications of ML in THz cancer imaging.

References	Algorithm	Application	Results
[77]	• Multinomial Bayesian learning algorithm	• Breast cancer	• Model outperformed the models 1D MCMC, 2D EM
[78]	• PCA and ML classifier	• Breast cancer	• Precision, sensitivity and specificity of 92.85%, 89.66% and 96.67% respectively.
[17]	• KNN and ANN algorithms	• Breast cancer	• Accuracy of 98.2% and 96.4% for ANN and KNN respectively.
[79]	• Markov random fields and Gaussian mixture model	• Breast cancer	• Model outperformed existing models
[80]	• SVM and Bayesian neural network.	• Breast cancer	• Accuracy 97.3%
[81]	• PCA and least squares SVM (LS-SVM)	• Prostate cancer	• Accuracy 92.22%
[82]	• SVM	• Cervical carcinoma	• Sensitivity and specificity of 88.6% and 96.7% respectively
[83]	• Gabor filter and ANN	• Skin cancer	• Accuracy of 94.117% for ANN

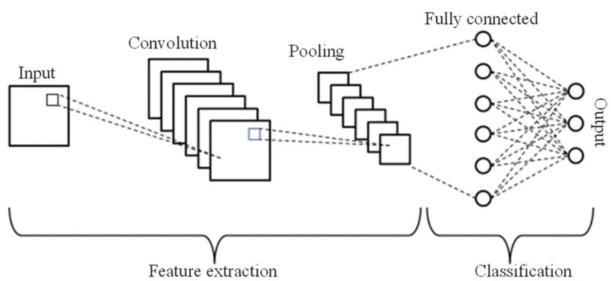

FIGURE 3. The architecture of CNN.

many output images are obtained termed feature maps or channels where each feature map represents its input modeling result. Pooling is then applied to compute the average or the maximum of pixel values thereby reducing dimension and increasing the modeling invariance by small signal change [2]. At the end of the CNN network, the fc layers are connected to determine the final output. Back propagation is used to determine the parameters such as filter coefficients. In more detail, the CNN architecture is made up of the layers:

- *Input layer*: input image to the CNN network is usually of 3 channels; red, green and blue (RGB)
- *Convolution layer:* in the convolution layer, weights are contained which extract image distinguished features, evaluating the local neurons output.
- *ReLU:* Rectified Linear Unit function is a commonly used activation function for introducing non-linearity by thresholding at zero.
- *Pooling:* allows down sampling of spatial dimensions. The pooling types include max, mean and stochastic pooling which helps to reduce the feature maps dimensions while getting robustness.
- *Flattening:* the 3D matrix is reorganized to vector.
- *Hidden layers:* layers cascade between input and output layer make up the hidden layers.
- *Fully connected layer:* determines the output.

The most common networks based on CNN include AlexNet, GoogleNet, VGG, Inception-ResNet-v2 and ResNet have been investigated for various medical imaging tasks. The extensive review of all deep learning techniques and their architectures has been reported by [87].

IV. DEEP LEARNING IN THZ SPECTROSCOPY, IMAGING AND SENSING APPLICATIONS

THz spatiotemporal and spectral datasets can be complex and extensive, thus deep neural networks can be employed as they are more robust than task specific. They provide improved learning efficiency and speed relative to conventional machine learning models. Moreover, they are capable of automatically learning and creating new features by themselves and deep learning outperforms machine learning algorithms in terms of training and testing accuracy.

Although deep learning models provide excellent efficiency and accuracy, they require large sets of labelled training data. This is especially valuable in THz based applications of deep learning as the THz datasets are still limited. Advances in deep learning have however introduced novel learning models such as transfer learning that provide even more training speed and enhanced performance with limited datasets [2], [90]. The application of various deep learning architectures has been explored in various THz imaging-based tasks as shall be discussed in this section. These applications have been classified into the following tasks: (1) design of metamaterials, (2) classification, detection and recognition where sets of data are categorized into different classes and localization or identification whereby the objects of interest are located, (3) high resolution image reconstruction, (4) parameter extraction, (5) denoising and (6) segmentation for extracting the region of interest. These tasks are explored in THz imaging, spectroscopy and sensing applications including non-destructive testing (NDT), security inspection, material and substance identification as well as biology & medicine applications.

Additional tasks that have been previously explored using deep learning include optimization of wireless communication systems.

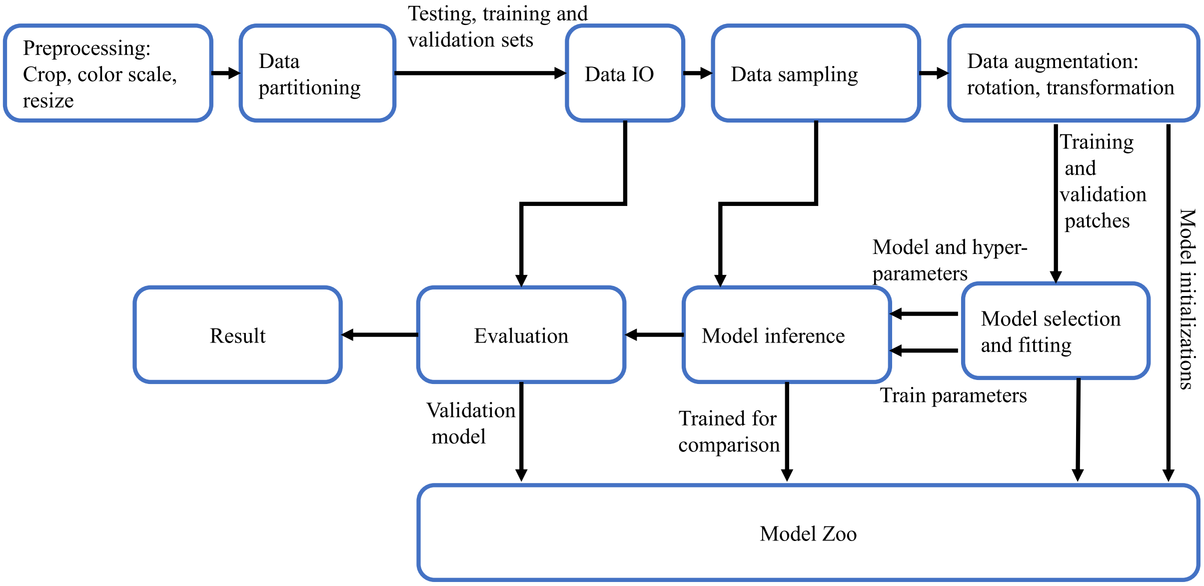

FIGURE 4. The pipeline of deep learning tasks.

The classification, detection, recognition, and prediction etc. tasks based on deep learning have different targets, but they follow an overlapping implementation pipeline as shown in Fig. 4. The preprocessing step is the initial and crucial step of developing deep learning models which is employed to improve the image quality, remove unwanted noise and irrelevant background parts from the images as well as for dimensionality reduction. The preprocessing computational operations include resizing the image, colour scale conversion, image contrast enhancement, filtering for noise removal, image restoration, morphological operations etc. After preprocessing, the data is partitioned into training, testing and validation sets which will be used as data input/output (I/O) and gets sampled. To increase the dataset size for increased model complexity, data augmentation is applied through various computational operations including rotation, scaling, shearing, translations, and geometrical transformations etc. to obtain training and validation patches. The parameters of the deep learning model get selected and specified then the data training is initialized, after which the model evaluation is performed using the validation dataset and results obtained.

A. DEEP LEARNING IN THz METAMATERIALS APPLICATIONS

Metamaterials (MM) are artificial electromagnetic materials that have special physical properties such as negative permeability, super absorption, optical magnetism, anomalous reflection and negative refractive index. The development of MM has recently become a research hotspot in THz technology for development of THz devices for example label free, highly sensitive biosensors based on split resonant rings for applications like cancer cell detection, lipids identification, virus detection and quantification of aflatoxin [91]. MM have also been explored using optical waveguides, optical buffers, slow light devices, optical sensors and detection, switching, opto-chemical sensors, thermo-optical modulators and cloaking devices etc. [92], [93], [94], [95].

The application of deep neural networks for optimizing the design of metamaterial structures has been recently investigated in a couple of studies for example the design of THz metamaterial absorbers have been reported in [96]. The design of chiral metamaterial induced asymmetrical transmission (AT) based on a deep learning approach has been investigated to accelerate chiral metamaterials design [97]. The proposed deep learning framework included bidirectional networks i.e. spectra network (SN) and an extended network (EN) with the capability to decipher the non-intuitive relationship between chiral metamaterials and their associated electromagnetic responses autonomously. Their model showed the ability to accurately predict metamaterial THz responses and inversely retrieve structure parameters with more efficiency than conventional metamaterial design approaches based on physical designs.

Figure 5 shows the framework of the deep learning model that can be used to automatically design chiral THz metamaterials developed by [97]. The network weights or data are represented by the blocks and the network neurons represented by the circles. The model is made up of bidirectional networks SN and EN as shown. In (a), the SN data flow follows a forward path that contains tensor down sampling (TDS) and a tconv up sampling (TUS) modules for converting structural parameters to response spectra. The inverse path with the aid of a well-trained forward path of the SN can effectively solve many to one problem in MM design (b) shows the EN structure where the forward path can accurately predict THz MM's asymmetric transmission spectrum

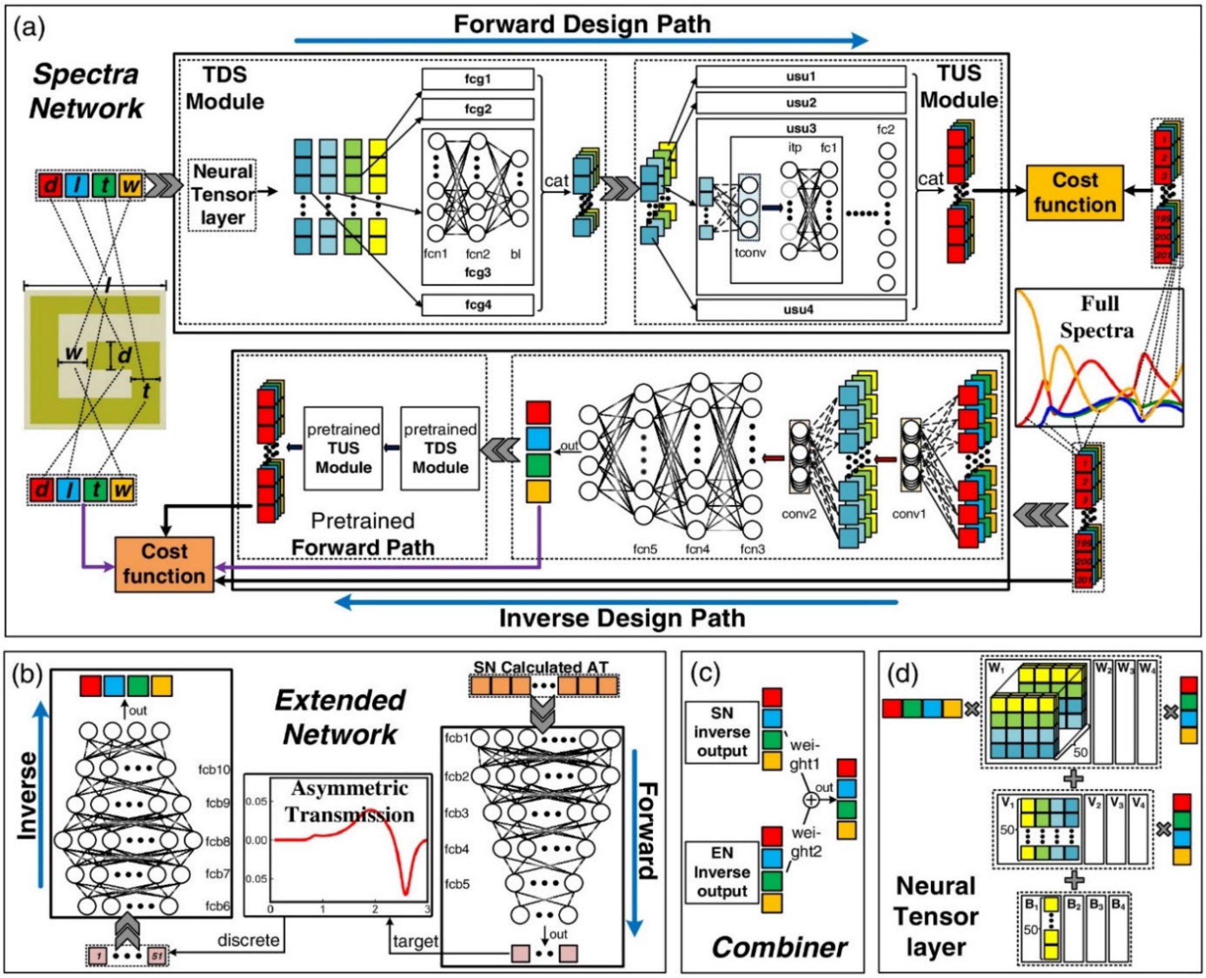

FIGURE 5. Deep learning based framework for chiral THz metamaterial design [97].

and the structural parameters from the desired AT directly retrieved by the inverse path. (c) shows the combiner that can combine the weighted sum of the SN and EN retrieval parameters. In (d), the neural tensor layer details in the SN TDS module is shown, with fcg 1-4, bl, usu1-4, fcn, fcb, tconv, conv and itp being the fully connected layer groups, bottleneck layer, up sampling units, fully connected layer, fully connected layer followed by batch normalization layer, transposed convolutional layer, convolutional layer and interpolation respectively [97]. In related works, the application of deep learning techniques was explored for metamaterials and metasurfaces structures and designs. In [98] and [99], a neural network was applied to predict absorption of a metasurface based on THz Graphene and showed capability for performing inverse design of the structure based on the absorption spectrum of interest. Deep learning was explored to optimize the design process of metasurfaces [100] and an AI based paradigm for THz smart sensing was designed using a crypto-oriented CNN for securely and accurately identify metamaterial in mixtures [101]. An inverse design of metasurface and neural network based design parameters for future multifunctional THz devices are also investigated by [102].

The target driven conditional generative network (TCGN) was used for reverse design of a chiral metasurface structure [103]. As shown in Fig. 6, each network is made up of input, output and hidden layers. The Generator's hidden layer consists of five fc layers and an embedded layer. Similarly, the hidden layer of the discriminator is made up of five fc layers and only one fc layer in the Target Extractor. The method was shown to enable efficient design of chiral metasurface structures on demand with good scalability and reverse design realization based on the TCGN deep learning [103]. A THz hologram reconfigurable imaging has been proposed in another study using discrete dielectric lens antenna design with deep learning (diffractive deep neural network) [104]. The application of deep learning for the optimization of metasurface and surface structure and design process has been explored by [105], proving the capability of neural networks to accelerate the design process and optimize the structure of metasurface structures.

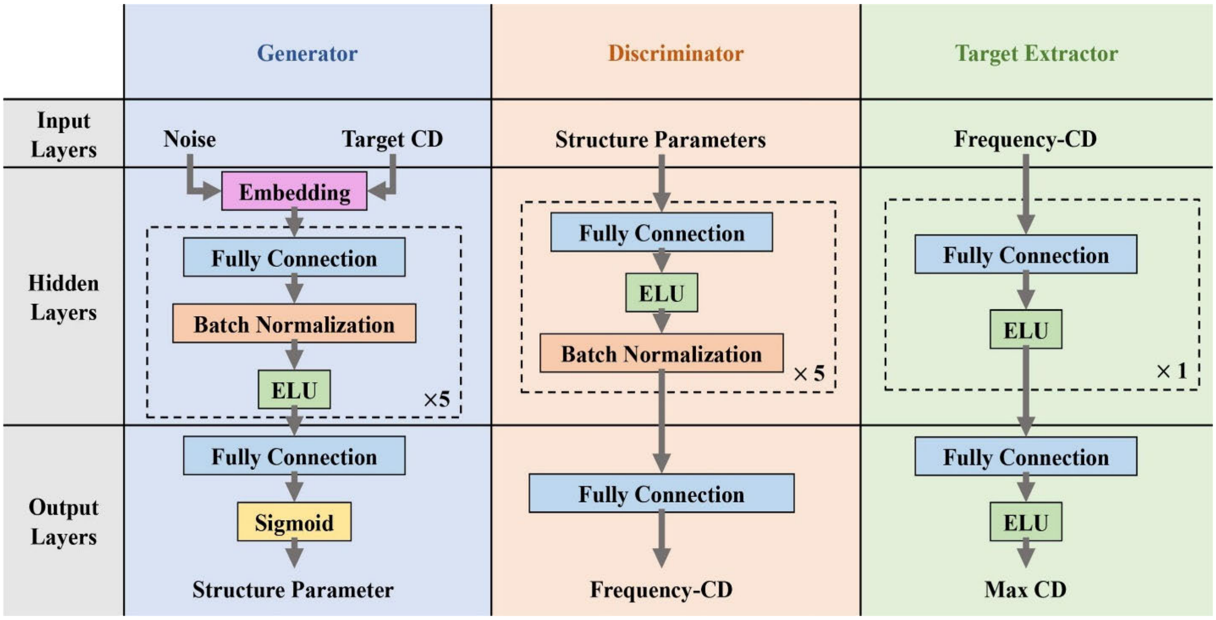

FIGURE 6. Detail of the TCGN model [103].

B. CLASSIFICATION, DETECTION AND IDENTIFICATION

Deep neural networks have been applied for classification, detection, recognition, identification and related tasks like characterization, prediction, and analysis in the THz spectrum. A neural network classification algorithm was used as a diagnostic tool to accurately differentiate between levels of thermal injury and simplify the diagnosis process based on a THz portable handheld spectral reflection scanner [106].

Figure 7 shows the flowchart of the neural network-based classification of burn injuries. The images were acquired using THz TDS which were denoised and band-pass filtered. Fourier transform was applied on the THz time domain signals and de-convolved using the Wiener algorithm. From each burn, up to 8 regions of interest were randomly selected and their mean preprocessed spectra used as input to the neural network with burn depth as the ground truth for classification. The model showed robustness with area under the curve (AUC) and receiver operation characteristic curve (ROC) (AUC-ROC) of 91%, 88% and 86% for partial, deep partial and full thickness burn classifications respectively [106].

In [107], the detection of the internal defects in a glass fiber reinforced polymer using THz time domain signals has been explored. The performance of three neural network models have been compared and the 1D CNN outperformed LSTM RNN and bidirectional LSTM RNN models based on recall and F1 score (harmonic mean of precision and recall scores i.e., $F1 = 2(\frac{precision \times recall}{precision + recall})$) metrics. The YOLO-MSA network has been investigated for detection of minor defects with high accuracy at real time speed for industrial online detection systems [108] and the YOLO V4 used for printed circuit board (PCB) defects detection in THz nondestructive testing application [109]. The recognition of tissue burns has been investigated using CNN which proved to be more robust than existing algorithms in [110]. Recognition of indoor objects has been addressed using THz based synthetic aperture radar and machine learning algorithm for localization and detection of the target object [111]. Deep neural network models have also been explored for automated classification of glucose [112] and materials based on THz TDS [113]. CNN has been used for drug detection such as anti-tuberculosis fixed dose combinatorial formulation based on THz TDS [114], detection of a foodborne pathogenic bacteria [115]. Deep earning models have also demonstrated precise and efficient predictions of resonant mode characteristics i.e. loss, frequency and electrical distributions for THz QCL lasers with distributed feedback [116]. The characterization of kernel size of the convolutional layers for THz deep learning models for high precision THz tomography was presented by Hung and Yang [117] and Transfer learning was demonstrated for automatic recognition of defects hidden in fiber reinforced polymer based THz nondestructive technology [118]. The security inspection based on deep learning and THz imaging technology is another application that has been leveraged to detect dangerous goods and hidden dangerous objects with accuracy and speed that meets the optimum security check requirements [119], [120], [121], [122], [123] as well as in industrial inspection THz applications for recognition of defects in integrated circuits (IC) [124], plastics and ceramics in real-time manufacturing process [125], [126] and nondestructive testing of impurities in wheat grains [127].

Deep learning techniques have been applied in the THz spectrum for identification and localization of different materials and substances. In [128], the attention bidirectional long short term memory (BiLSTM) and a CNN based model were used for identification of antibiotics in the THz spec-

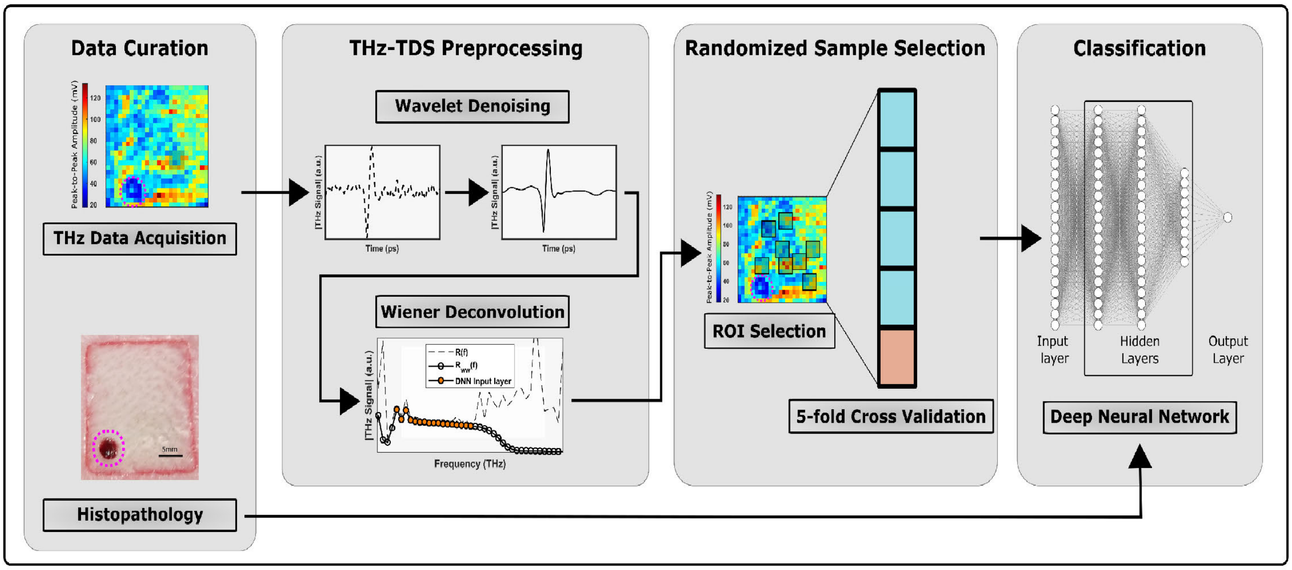

FIGURE 7. The signal processing pipeline for classification of burns [106].

trum. The model confirmed better interpretability and strong recognition with an F1 score of 0.98. Figure 8 shows the architecture of the CNN-BiLSTM-Attention model which is made up of three main layers. The first layer is a CNN based feature dimension reduction layer that performs model computational complexity reduction. The feature extraction layer uses the BiLSTM to extract features and the attention mechanism (AM) and BiLSTM to obtain the data sequences of the antibiotic [128]. Localization of biosensors in the human blood stream for anomalies detection in the body has been introduced which exploits inertial positioning and sub THz backscattering [129].

Another study proposed the deep learning method called Structured Intra-Attention Bidirectional Recurrent (SIABR) for three dimensional (3D) THz indoor localization application [130]. The 3D localization demonstrated accuracy and network model showed robustness and fast convergence. The application of machine learning techniques has also demonstrated high performance when investigated for agricultural application for precise identification of plant species at cellular level in the THz frequency range 0.75-1.1THz [131]. Identification of crude oil spills using THz and deep learning were explored to identify the pollution location for increased environmental protection and monitoring [132] and the identification of THz tags was investigated by [133] and radio frequency identification (RFID) tags [134] as well as materials identification [135].

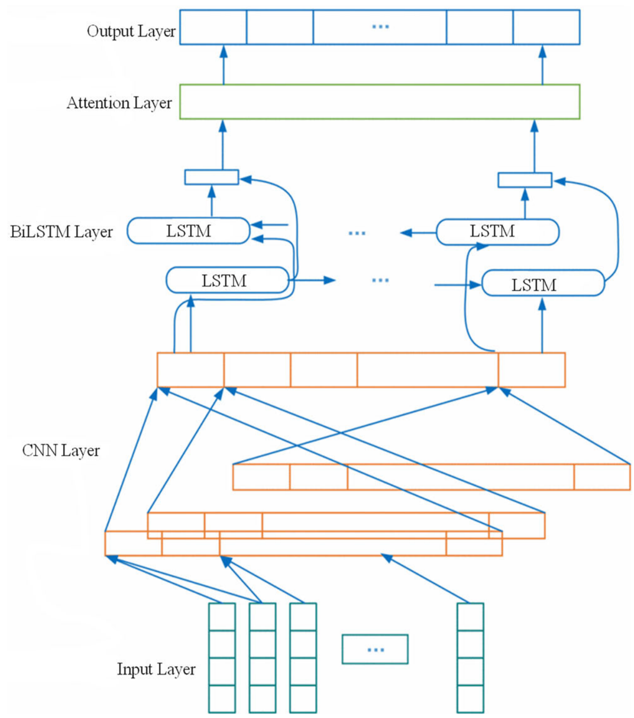

FIGURE 8. The CNN BiLSTM-Attention model architecture [128].

C. HIGH AND SUPER RESOLUTION THz IMAGE RECONSTRUCTION

Deep learning tools can potentially be used to alleviate the limitation of low spatial resolution that plagues THz imaging applications towards high and super resolution THz image reconstruction. In [136], the super resolution of THz images was demonstrated based on CNN through adjusting the interpolation parameter of the network.

Figure 9 shows the framework of the adjustable or accommodative deep residual CNN network for real aperture THz super resolution imaging. The architecture of the basic network (Nb) is on the left side of the figure. When the pixel shuffle layer of the network is slightly adjusted, the down sampling interval (Ds) are applied and optimization of all the network parameters is achieved. This is achieved through the training process where the loss function of reconstructed images and high-resolution images are minimized iteratively. The right-hand side of the architecture is the layout of the adaptive network (Na). The simulation and tested data acquired using a frequency modulated continuous wave (FMCW) real aperture scanner demonstrated effectiveness and superiority of their method quantitatively and qualitatively [136].

The reconstruction of THz images based on deep learning for superior image quality through high and super resolution image reconstruction was also explored for; 3D THz image reconstruction [137], THz CT 3D image reconstruction [138], [139], [140] and 3D THz aperture radar imaging [141], [142]. THz coded aperture radar imaging. Deep learning techniques have been applied in; residual learning based THz spectral image reconstruction [143], improving the resolution for defect detection [144], [145], in THz nondestructive testing applications [146], [147], in industrial applications for example IC manufacturing [124], [148], [149], [150], in security inspection applications [151] and various THz imaging applications [152], [153]

D. PARAMETER ESTIMATION OR EXTRACTION

The estimation and extraction THz related parameters has also been explored [154] including the model parameters associated with materials from FMCW THz data was proposed that uses deep optimization based on a neural network [155]. In [156] estimation of the number of layers in THz TDS layer thickness measurements were determined using a feed forward neural network and the approximations for material parameter extraction were performed artificial neural networks [157]. Mikerov et al. proposed neural network based fast, post measurement technique for removing effects of water vapor on THz TDS to enable dry atmosphere measurements [158].

E. DENOISING

The THz images can be recorded through strongly scattering medium and the THz measurements can be noisy with low signal to noise ratio (SNR) and can be performed imperfectly under real operational conditions [65]. These and other factors are sources of noise and can cause low transparency causing distorted measurements and making discrimination of objects and regions complicated. Deep learning can be attractive to enable low noise measurements and resolve objects. In [159],a neural network known as WaveNet and the CNN were used to enhance a noise degraded THz signal through deep learning for the acquisition of high SNR THz signals without having to increase the measurement time. A CNN was proposed for reducing artifacts and noise in THz TDS and THz imaging applications showed the effectiveness of the method for improving the under-sampling THz image quality and allowed high acquisition rates [86]. In another study [160], a multistage network called DInet was used THz image restoration of degraded THz images from blurring effects like noise, diffraction phenomena and intrinsic long wavelength. The point spread function of THz imaging was first reconstructed and DINet designed for image restoration on THz datasets.

F. DIMENSIONALITY REDUCTION/SEGMENTATION

Medical images play a significant role in medical diagnosis; however, their acquisition is often affected by imaging equipment and local volume effects etc. which causes problems like edge blurring to be inevitable. The segmentation is crucial for extracting valuable regions of images or image objects through partitioning, giving the object details like location and boundaries. This facilitates analysis, identification tasks and also useful in obtaining size of the region of interest for example size, volume which are helpful for diagnosis and treatment [161]. The segmentation can be as simple as cropping out the region of interest and as complex as the application of algorithms. The algorithms traditionally used for segmentation include Region based (region growth and threshold segmentation), morphological approach, edge detection and segmentation based on clustering. Clustering based segmentation techniques include Fuzzy C-means clustering and nuclear method Fuzzy C-means clustering.

The blurred margins often compromise the segmentation of the region of interest particularly when traditional segmentation techniques based on statistical inference are used. Moreover, it is a challenging task to perform segmentation on tumors that have invaded the muscular tissue. The deep learning techniques prove to provide improved performance in these challenging tasks. The automated segmentation of THz images have been recently explored for example using deep learning for automatic segmentation of THz glioma images [64]. In [84], the breast cancer tissue segmentation and classification was investigated using a deep CNN models to perform pixel wise classification of THz spectrograms obtained through image preprocessing based on the wavelet synchronous squeezed transformation (WSST).

The preprocessing approach converts THz time sequential data of each THz pixel to a spectrogram, the spectrograms were then used as the input tensors to the network models to perform pixel wise classification to achieve a cancer tissue segmentation map. The Inception-ResNet-v2, ResNet-50 and GoogleNet pretrained CNN based network architectures were modified for training through replacing the last fc layer that connects directly to the classification results. By doing so, the learnable parameters from fc layer can adjust themselves two times quicker than those in the convolution layer during back propagation training. The performance of the investigated CNN models was evaluated using the leave one sample out cross validation and other evaluation metrics including precision, accuracy, size and intersection which demonstrated improved performance relative to the conventional statistical methods. The results showed improved segmentation of cancerous tissue regions and muscle in xenograft tumors [84].

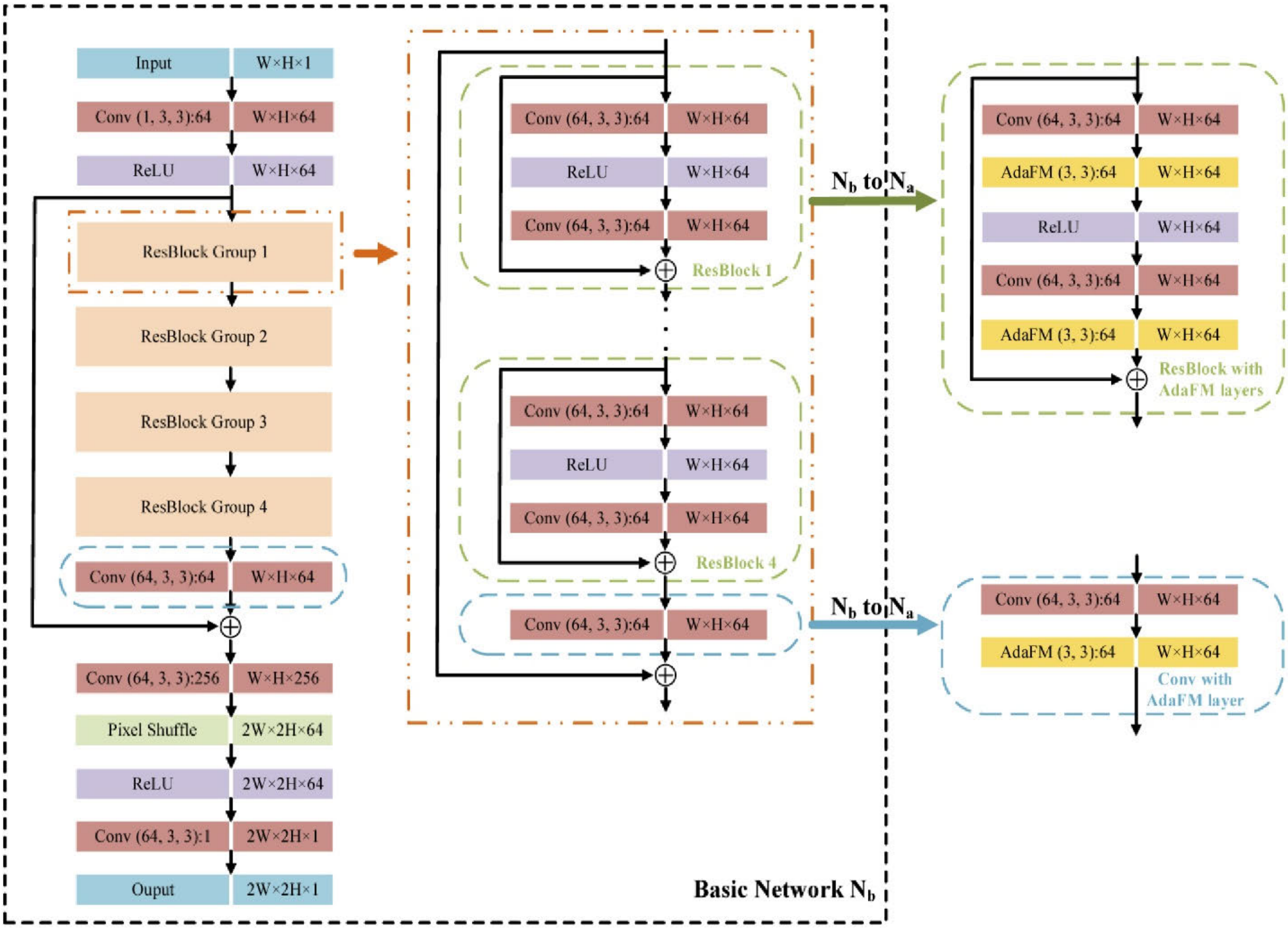

FIGURE 9. Architecture of the CNN network for THz super resolution imaging [136].

G. OTHER DEEP LEARNING APPLICATIONS IN THZ

The application of Deep learning in the THz spectrum have also been explored for wireless communication and next generation network applications for example a deep learning based autoencoder for fiber –THz integrated 6G radio access network at 220GHz [162] CNN based THz channel estimation and optimization [163], [164], [165], deep learning based design of THz based 6G wireless communication [10], [166], [167], [168], [169], [170].

V. METRICS FOR PERFORMANCE EVALUATION IN DEEP LEARNING

The evaluation metrics measure the performance in terms of accuracy, sensitivity, specificity etc. of the developed deep learning or machine learning model.

A. CONFUSION MATRIX

The confusion matrix consists of ground truth class in the rows of the matrix and estimated class in the column.

In Table 3, suppose a classification with J classes would imply C_i inputs in testing dataset out of $\sum_{j=1}^{J} c_{ij}$ trials, c_{ij} would be classified as C_j. The rate of correct classification for each class C_i known as a recall is expressed as; $c_{ii}/\sum_{j=1}^{J} c_{ij}$. The average recall for all classes known as mean accuracy denotes the overall performance for classi-

TABLE 3. Confusion matrix examples for multiple classes.

True \ Estimated	C_1	C_2	$\cdots$	C_J
C_1	c_{11}	c_{12}		c_{1J}
C_2	c_{21}	c_{22}		c_{2J}
$\vdots$				$\vdots$
C_J	c_{J1}	c_{J2}	$\cdots$	c_{JJ}

TABLE 4. Confusion matrix examples for binary classes.

True \ Estimated	Positive	Negative
Positive	a	b
Negative	c	d

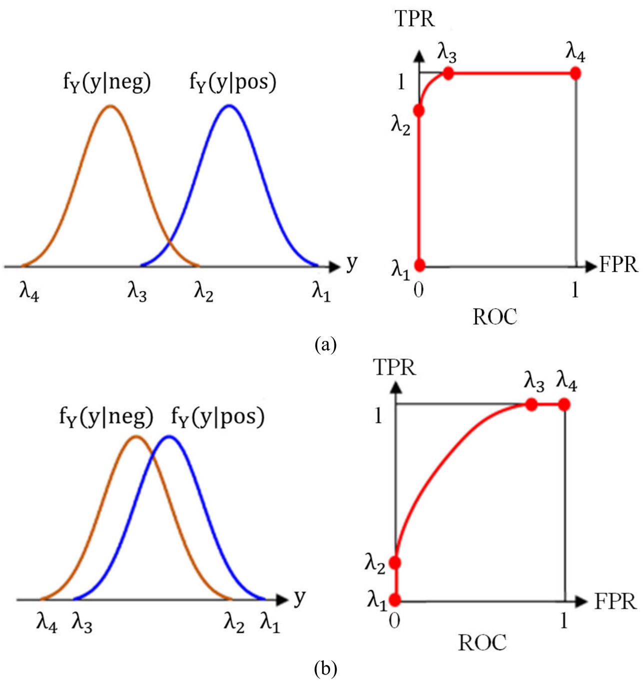

FIGURE 10. **ROC examples from different PDFs. a) with small overlap between the PDFs and b) much overlap [3].**

fication with multiple classes. For the binary classification (Table 4), the metrics used for evaluation are true positive rate (TPR), the false positive rate (FPR), the respective true and negative rate (TNR and FNR) which are as expressed follows [3]:

$$TPR = a/(a+b) \text{ i.e., sensitivity}$$

$$TNR = d/(c+d) \text{ implying specificity}$$

$$FPR = c/(c+d) \text{ i.e., } 1 - \text{specificity}$$

$$FNR = b/(a+b) \text{ i.e., } 1 - \text{sensitivity}$$

B. ROC AND AUC

For binary classification, determination of the threshold λ, on which classification decision is based i.e., whether positive or negative affects the classifier performance.

Considering γ a random variable of y, with two conditional probability density functions (PDF) denoted as $f_\gamma(y|pos)$ and $f_\gamma(y|neg)$ for y given positive and negative true class of input. TPR the area of $f_\gamma(y|pos)$ for $y \geq \lambda$ and FPR $f_\gamma(y|neg)$ for $y \leq \lambda$. The curve is plotted for TPR against FPR for λ values known as the receiver operating characteristic curve (ROC) as illustrated in Fig. 10.

C. COEFFICIENT OF DETERMINATION

Usually denoted by R^2, the coefficient of determination is a metric for performance evaluation that uses regression in which the average deviation is measured between target and estimated values. Suppose for *nth* dataset instant, the target and estimated values are y_n and y'_n respectively, the estimation error $e_n = y_n - y'_n$ and R^2 as given in equation below for all the testing dataset instances. R^2 gives the effectiveness measure of the estimated value in comparison to a baseline estimator through which y_n is predicted as $\bar{y}$ for all the values of n. $R^2 = 1.0$ implies a perfect estimator, $R^2 = 0.0$ for baseline estimator and negative value for R^2 worse estimator.

$$R^2 = 1 - \frac{\sum_n e_n^2}{\sum_n (y_n - \bar{y})^2}, \bar{y} = average\,(y_n) \qquad (1)$$

D. K-FOLD AND LEAVE-ONE-OUT CROSS-VALIDATION

Considering small occurrences in a given task, the training and testing data will be insufficient to reliably evaluate the performance of an ML model, in this case, a k fold cross validation whereby many training and testing trials can be done using different datasets is used [171]. k equal subsets of the dataset are divided, and one subset is assigned to testing set, the remaining $k - 1$ for training and then train the model as usual. The process is then repeated k times using each k testing set to obtain k models and their performance then get the average of the performances as the final performance. When the dataset is too small, the leave-one-out cross validation (LOOCV) is utilized for evaluation [171].

VI. OPEN RESEARCH CHALLENGES AND OPPORTUNITIES

The THz imaging shows great biomedical research potential as well as clinical potential through its unique spectral features for example non-ionizing, non-invasiveness and label free medical imaging and cell detection [210]. The ability of a medical imaging tool to detect cancer accurately and rapidly is critical for early diagnosis, early care and monitoring progress of treatment. The existing technologies mostly depend on ionizing radiation and biological or chemical labelling like use of nuclides which can adversely affect biological tissue and cell functions and activities thus limiting them to molecular resolution. To elaborate further, a comparison of the advantages and limitations of THz radiation-based imaging compared to existing technologies that are based on ionizing radiation such as X-Ray and Computed Tomography (CT) in the context of biological imaging can be summarized as follows:

Advantages

- Non-ionizing and non-invasiveness due to low photon energy
- Sensitivity to bipolar molecules like water enabling high contrast between diseased and normal tissue.
- Spectral parameter precision, for example measurements of amplitude and phase can be simultaneously obtained.
- Spectral fingerprinting whereby the spectra of different cells are unique.
- Can be easily interfaced with analytic systems.
- Has early molecular detection capability.

- Outstanding ability for surface imaging
- Label free detection.
- Less scattering loss.

Disadvantages

- Relatively insufficient penetration depth (macro level), low spatial resolution, poor SNR.
- Long image acquisition times.
- High equipment costs.
- Immature technology, lack of standardization of measurements, measurement protocols, processes or models for comparability, reproducibility, and possibly clinical adoption.
- Strong absorption of THz waves by water
- Lack of established databases or repositories to facilitate data driven academic research.

Previously reported studies have illustrated the feasibility of THz based technology for cancer detection including skin cancer, breast cancer, glioma, gastric, digestive, cervical cancer etc. with ability to clearly delineate the cancer margins [172].

The application of conventional machine learning algorithms that are based on statistical inference has been leveraged in THz imaging, spectroscopy and sensing applications as previously presented. The performance of such techniques however relies on the accuracy of dataset preprocessing, feature extraction and segmentation prior to subjection to the classification model. The recent exploration of deep learning-based models has shown to outperform traditional machine learning techniques are outperformed based on various performance evaluation metrics like accuracy. Moreover, deep learning models are more robust than task specific and they are capable of automatic feature learning and extraction, therefore they can be used for heterogeneous and multimodal data applications.

Being a class of interpolation algorithms, the deep learning can be found an attractive tool in the THz technology for various applications in complex tasks like classification, detection, noise removal and high-resolution image reconstruction etc. as reported in this work. The use of deep learning techniques in THz technology applications can help alleviate the problems associated with THz technology such as low, diffraction limited spatial resolution, slow acquisition speed etc. and can be useful for designing compact diffractive elements, efficient THz emitters and detectors, improve quality of recorded data and reach super resolution. In the THz technology fraternity, deep learning algorithms have been explored in non-destructive testing, security inspection, material/substance identification, metamaterial design and wireless communication applications. Its application in biomedical applications, particularly THz cancer imaging related tasks like cancer classification, characterization, detection, prediction etc. are still scarce. Here we discuss some of the challenges limiting the exploration of deep learning techniques in THz imaging for cancer, the alleviation of which will pave way to future research scope.

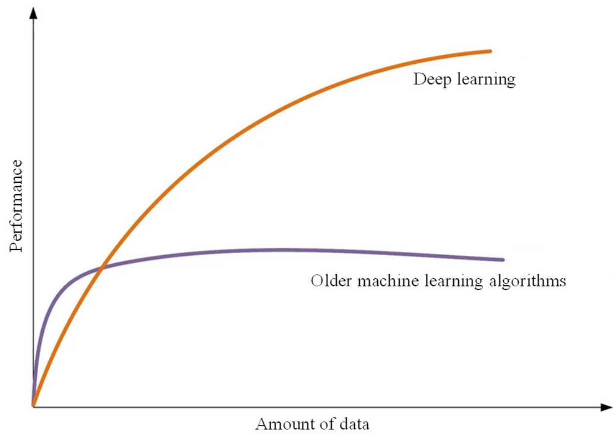

FIGURE 11. **Performance of deep learning according to amount of data.**

A. UNAVAILABILITY OF SUFFICIENT TRAINING DATASETS

The deep learning networks are extremely data hungry and involve representation learning thus require extensively large training datasets for achieving well behaved performance of the models [87]. The unavailability of sufficiently labelled THz cancer image datasets is one of the major challenges inhibiting the exploration of deep learning for THz cancer image applications in academic research. Efficient creation of THz cancer image database is expensive and involves complex processes.

Due to this limitation most previously published works have focused on shallow machine learning and statistical based techniques to perform classification, segmentation and detection tasks in THz imaging studies which do not require huge datasets [3]. Figure 11 shows the relation of model performance to the amount of data for deep learning and conventional machine learning algorithms like SVM, k means and kNN etc. As can be seen from the figure, for deep learning algorithms as the data increases a well behave performance model can be achieved. In THz cancer imaging studies, the unavailability of sufficient datasets limits the exploration of these models for academic research. At the time of writing this paper to the authors' knowledge, there are no shared labelled THz cancer image datasets unlike in other modalities like MRI, CT and X-Ray which have well established, publicly shared datasets that support data driven research. The unavailability of sufficient THz image datasets is mostly due to the fact that the technique is not yet fully established, more factors contributing to the unavailability of sufficient training THz datasets include:

- High cost of commercially available THz equipment i.e., from \$100000 to \$600000.
- The current sources of samples include human tumors from freshly excised tissues obtained from hospitals and Biobanks, animal models based on xenograft and

transgenic and from phantom models made from material that mimic fresh tissue. The processes involved in obtaining the sample are still complex and difficult due to hospital regulations, restrictions and high tissue costs from Biobanks.
- The use of freshly excised tissue samples is associated with long processes, for example firstly going through histopathology process and sample preparation process like staining and embedding which require special environmental conditions.
- The data acquisition methods and procedures in THz imaging are not yet standardized and are still complex.

To address the data unavailability limitations in THz cancer imaging, we suggest four approaches that could facilitate academic research. First, the employment of Transfer learning based on deep learning whereby one pretrained deep learning network model is used as a starting point for developing a training model. This can be achieved by fine-tuning a pretrained model such as AlexNet, GoogleNet and ResNet to learn a new task such that the acquired knowledge from one domain (source) gets transferred to the target domain even when there is a disjoint feature space and data distribution of source and target. The network retraining using transfer learning is easier and faster than developing and training the model from scratch. Moreover, it enables less and imbalanced training data usage and reduces computing resources and training time [90]. Secondly, data augmentation tasks can be performed to increase training dataset size through image rotation, scaling, translation, and mirroring etc. This improves the model performance and accuracy while the image original label is not changed. Thirdly, generation of synthetic datasets through simulations can increase training dataset volumes required for deep learning-based simulation. Lastly, the implementation of multimodal data fusion can also be considered to alleviate the data shortage challenges in data driven THz cancer imaging studies by taking advantage of the automatic feature learning capability of deep learning models. This does not only address the THz dataset shortages but also enhances model complexity and makes the deep learning model robust than task specific.

B. IMBALANCED DATA

Another challenge in applying deep learning models in THz imaging for cancer studies is imbalanced data. Biological data tend to be commonly imbalanced as generally there are more numerous negative samples than positive ones [173]. When a deep learning model is trained over imbalanced datasets, undesirable results may be obtained. To solve the imbalanced dataset limitation in THz cancer imaging applications, the following techniques can be used for example employing the correct criteria for result prediction and evaluating the loss such as the area under curve (AUC) as the criteria and resultant loss. Weighted cross entropy loss should also be employed which ensures good performance of the model with small classes. Large classes can be down-sampled and small classes up-sampled. To make the model handle imbalanced datasets, some methods such as constructing models for every hierarchical level since biological systems have hierarchical label space [87], [174].

The issue of imbalanced training datasets in deep learning based THz image applications for breast cancer study has been encountered by Liu et al. [84], which was solved through adopting the weighted cross-entropy loss function for training the classifiers. An equal weight of each sample was implicitly assigned when the leave one sample out cross validation was performed. The deep learning-based segmentation was evaluated in two-class and three class categories due to their highly imbalanced amount of THz scan signals in the muscle class.

C. OVERFITTING

Due to a vast number of correlated and complex parameters as well as lack of training data, deep learning models often have high chances of resulting in overfitting of data during training stage which reduces the performance of model on testing data [175]. Over fitting of training data prevents the classifier to be generalized to new samples. High complexity and flexibility of a deep learning model was also considered to bring high risks of overfitting [174]. When proposing deep learning for THz cancer imaging applications, this problem should be accurately handled and considered by developing techniques that handle the problem. Deep learning models can overcome overfitting through implied bias of the training process [175], [176] Some techniques have been reported to ease overfitting including based on model parameters and architectures such as batch normalization, weight decay and dropout [87]. Model input based techniques such as data augmentation and corruption and model output based techniques that regularize the model though penalizing the over confident outputs [177]. To avoid overfitting by increasing the amount of training data through augmentation, data augmentation techniques which are data-space solutions incorporates a couple of methods for improving size and attributes of training datasets. The data augmentation techniques include but are not limited to flipping, rotation, color space augmentation, translation, noise injection and cropping. When such techniques are used, deep learning networks can perform better. The Siamese network was used expand the training dataset and prevent overfitting without using traditional data augmentation techniques in a deep learning based THz cancer imaging study [84], [174].

D. INTERPRETABILITY OF DATA

The deep learning techniques are in fact interpretable though occasionally analyzed as a black box. A method is however required to interpret deep learning to obtain valuable patterns and motifs that are recognizable to the network. In disease prediction or diagnosis tasks, this will be helpful to enhance accuracy of prediction outcomes which are the basis of the model decision. Scores of importance for each portion of a particular example can be given for example through perturbation or back propagation based techniques to achieve the outcomes with enhanced accuracy [178].

E. UNCERTAINTY SCALING

When employing deep learning techniques, the final prediction label is required together with the label of the score of confidence for each inquiry from the model to achieve prediction. The measure of how the model is confident in its prediction is the so called score of confidence and it's a significant attribute in preventing belief of misleading and unreliable predictions which reduces resources and time consumed in proving misleading prediction outcomes in various application scenarios [179], [180]. In THz cancer imaging and related applications, uncertainty scaling is crucial for evaluating automated clinical decisions and improving reliability of deep learning-based disease diagnosis. Due to overconfident prediction output of different deep learning models, the score of probability e.g., from the softmax output of a deep learning network is more often incorrectly scaled and thus requires post scaling for a reliable probability score. Several techniques can be used to output correct probability scores such as histogram binning, Bayesian Binning into Quantiles, legendary Platt scaling and isotonic regression, temperature scaling reported achieved superior performance for deep learning techniques [87].

F. MODEL COMPRESSION

Deep learning models require intensive computational and memory requirements for obtaining well trained models, this is because of the large number of parameters and huge complexity of the models. The healthcare application is one of the most data intensive fields which reduces the implementation of deep learning in limited computational power machines. Additional computation power is required to comply with vast sizes of heterogeneous data in healthcare. Modern hardware based parallel processing technologies have been proposed such as Field programmable gate arrays (FPGA) and Graphics processing units (GPUs) to alleviate the computational limitations associated with deep learning [181], [182]. Techniques for compressing deep learning models to reduce the model computational issues have also been designed such as parameter pruning, knowledge distillation, use of compact convolution filters and estimation of information parameters for preservation using low rank factorization [87].

G. OTHER CHALLENGES

Additional issues requiring proper attention that are associated with implementation of deep learning algorithms and applicable to THz medical imaging include catastrophic forgetting, vanishing gradient problem, exploding gradient problem and under-specification [87]. The deep learning methods enable visualization of results in a manner that can be conveyed to medical practitioners. Some challenges have been identified that affect accuracy based performance of these data driven techniques from THz imaging of breast tumors in [84]. These challenges have shown to cause "erroneous" classifications which are scattering near edges, tissue changes between THz imaging and histopathology, multiple tissues in THz pixel region, overlapping electrical property in fat and muscle tissues and classification of non-tissue related artefacts.

The machine learning and deep learning models in the imaging application domain are also vulnerable to attacks that can lead to either slight result discrepancies or the consequences can be lethal in applications where safety is critical. Such attacks can be subjected to the deep learning models at the edge, fog or cloud layers of the system and they include adversarial attacks, neural level Trojans, hardware attacks and intellectual property (IP) stealing [209]. The adversarial attacks are crafted adversarial machine learning attacks that compromise the model performances [207] in various machine learning applications, and the THz imaging application is no exception. The approaches to develop machine learning models that are adversarial robust have been reported that can restrain adversarial examples and perturbations to ensure model security and integrity [207]. Such adversarial robust approaches include modifying the training and testing data, modifying the features/parameters learned by the training model and use of additional auxiliary models to enhance the main model's robustness.

For the effective modeling of medical tasks, the challenges associated with processing heterogeneous observational data from real world clinical databases must be considered. These potential challenges include non-standardized data structures, small and incomplete datasets, preserving patient data privacy, cost effective annotation process, multimodal data and irregular health trajectories [183]. Despite the THz based imaging's massive clinical potential, the technology development is still at an early stage and still associated with a lot of limitations. The alleviation of current limitations can pave the way to future research. For spectral fingerprinting of cells, a spectral finger print database [72] is needed as a prerequisite for identification, however there are no standardized techniques for detection yet, thus the establishment of a standardized detection system would be essential. For spectral studies, the researchers still face challenges of extracting target spectral fingerprints out of interfering signals and complex backgrounds through Fourier transforms, which may be realized by future development of high sensitivity and specificity sensors like meta-materials and plasmonic antennas [72].

Due to the THz ability to resonate with water and biomolecule vibrational motion on picosecond and sub-picosecond, the THz imaging is able to contrast between pathological, healthy, burned and dehydrated tissues and able to measure the refractive index and absorption coefficient resulting in phase and amplitude information measurements. However, the water absorbs THz wave i.e., absorption of 300cm^{-1} at frequency 1.5 THz. The tissue preparation methods such as frozen, paraffin embedding and formalin fixing have been developed and contrast between tissues is on the basis of increased refractive index and absorption coefficient, likewise the strong THz absorption capability of water causes THz to only be able to penetrate a few millimeters of tissue and thus, in vivo measurements using THz are still more friendly for surface tissues.

The THz systems are attractive emerging modalities, however their application in medical imaging is still characterized by intrinsic limitations including bulky THz systems, poor source performance, low contrast mechanism, low detection sensitivity, poor signal-to-noise ratio and slow processing etc. Moreover, most experimental studies for THz cancer imaging have been performed ex vivo and in vitro, with the exception of epidermal observations that can be done in vivo. These limitations have been suggested to be overcome through nanotechnology supported THz modalities [211]. For example, the development and use of nanoparticle-based contrast agents such as gold nano-rods and super-paramagnetic iron oxide nanoparticles (SPIOs) have been explored for improving THz imaging contrast in vivo [172]. The use of nanotechnology in THz technology can also improve sources and detectors development including the development of nanoparticle probes.

H. FUTURE PROSPECTS

The developments in THz technology have made significant progress in various applications and trigger a plethora of promising research directions, particularly in the deep learning enabled THz cancer imaging. Advances in THz technology play a significant role in medical imaging for cancer diagnosis, treatment and follow ups to verify the success of a treatment. Additionally, medical images are now a key component to the invasive procedures in cancer for surgical and therapy planning, and image guided surgeries where the real time imaging is performed during the procedure. Conventionally, the diagnosis procedure is based on the review of the acquired images by a radiologist who performs interpretation, writes a report of their findings, then based on that, the physician defines the plan for diagnosis and treatment. However, with ever increasing and advancements of medical imaging techniques, it also implies more volumes and variations of image data for interpretation resulting in limitations associated with time for review, variations in interpretation, human subjectivity and fatigue. This leads to compromised findings, insufficiency of quantification and long result turnaround time which limits personalized healthcare that is evidence based. The application of AI tools, however, can automate image analysis thus providing support to the physicians. Moreover, the diagnosis systems where the physician coupled with an aiding system have been reported to provide more accuracy [88]. Some of the systems that can be developed to automate the analysis include, systems for quantification of the cancer extent, detection of the cancer pathology, pathology characterization for example, malignant & benign and decision support tools which enable 3D and time varying data to be characterized and quantified. The major limitation with developing these AI tools in THz imaging is lack of sufficient data, what we would refer to as the data challenge. However, some previously developed techniques could be enablers of deep learning and ML technology in the THz imaging space. Such enablers include the Transfer learning (TL) whereby pretrained network models are used to apply previously acquired knowledge to another problem that is reported in [184], [185], and [186]. The techniques based on TL include: ImageNet [184], [185], [186], [187] AlexNet [187], VGGNet [188], ResNet [189], InceptionNet [208], U-Net [191] and DenseNet [192]. A second solution is the emergence of synthetic data augmentation whereby schemes based on generative modelling for instance, the generative adversarial network (GAN) and use of variational encoders are used to synthesize data to increase training dataset [193], and thus improve the performance of the model. The development of integrated learning for domain adaptation models capable of discriminating heterogeneous feature spaces of different and multiple domains for cross modality cancer image analysis can also be applied as reported in [194] and [195]. Another solution would be the adoption of the novel federated learning in THz cancer imaging to combat limitations associated with data privacy, data access rights, data sharing and data security so as to facilitate academic research. The federated learning uses distributed computing and strategies of data aggregation so that a robust and common algorithmic model can be enabled without transfer of the data i.e., the algorithm is trained across decentralized devices etc. without exchanging data, which is contrast to uploading datasets to a centralized server [21], [88], [196], [197], [198], [199], [200], [201], [202].

The general need for automated detection and classification models, empowered by machine learning developments is an increasing trend in the biomedical imaging field. As reported in this work, since the THz imaging technology is novel, most of the similar studies have been explored over image datasets from conventional imaging modalities like MRI, X-Ray, Computer tomography (CT) and ultrasound etc. and in these applications, the algorithms that have been reported to be the mostly / commonly used and been reported to have given consistent, highest accuracy, specificity and sensitivity when applied to images from various modalities are the SVM and ANN algorithms [37], [38] followed by CNN recently. With the existing studies of ML based detection and classification in the THz imaging and spectroscopy application, most of the studies have been reported in non-destructive testing, security, material/ substance and object detection as well as in the biological studies where again SVM and ANN have been observed to be the mostly used. However, due to the few studies available in deep learning application for cancer detection and classification using THz imaging, the available data is not sufficient to conclude the model's performance evaluation and the commonly used algorithms considering the relatively small training datasets resulting in limited model complexity. Rather the developed models would be task specific than robust due to the limited sources of THz cancer imaging datasets caused by the high cost and maintenance of tissues as well as purchasing of the commercially available THz imaging equipment. We therefore recommend the fusion of common medical imaging modalities that are complementary with THz imaging so as to increase the training dataset sizes so that integrated deep learning frameworks can be developed, performance evaluation standardized and enable more automated diagnosis systems through the application of deep learning algorithms (which require huge training dataset sizes). Moreover, more work can be done in application of deep learning techniques to THz imaging for image, reconstruction, enhancement, registration, segmentation, recognition, automatic report generation and disease prediction.

The cutting edge quantum inspired deep learning approaches promises to resolve the limitations of deep learning based on parallel computer and GPU hard drive expense in future, where classical data is transformed to quantum state by the quantum routine, and after the quantum operations, the classical data is retrieved [161]. The deep learning models address the limitation of scalability in conventional ML which are task specific or scenario dependent, enabling adaptation to continuous updates in THz data. The long training times that are obstructing current deep learning systems from effectively operating in real time may be solved by developing real time deep learning techniques with shorter training time and improving the training process. The successful operation and deployment of next generation THz systems for cancer applications calls for better localization and sensing performance. Future research for the development of THz imaging, spectroscopy and sensing should expect migration towards advanced machine learning such as deep learning for automating analytical modeling and various solutions to current limitations. In this case of medical imaging where distributed yet preserving data privacy is of utmost importance, federated learning-based techniques can be adopted to facilitate research and model standardization. Further, the multitask and multimodal learning capable systems should also be leveraged for scalable models. The reinforcement learning based techniques will be useful in interactive learning frameworks for example, in indoor patient monitoring situations and THz multipurpose platforms.

The novel neural network structures such as the broad learning system (BLS) that consist of enhancement nodes and feature nodes and are based on pseudo-inverse theory and compressed sensing could also offer new opportunities in future THz cancer analysis. Compared to the popular deep neural networks, BLS networks are capable of incremental learning and has the ability to remodel the system without tedious process of retraining. Thus faster modelling speed, higher regression accuracy and better generalization for solving various tasks [203], [204]. Unified THz systems that can support various applications from in-home health, virtual reality services to residential security etc. with high reliability, high data rates and low latencies are expected to pave way for next generation research frontiers [2].

VII. CONCLUSION

In this article, we present a broad review of the recent applications of artificial intelligence particularly, the deep learning techniques in various targets of THz sensing, imaging, and spectroscopy applications. We note that the main focus of most reported studies is on the potential application of conventional machine learning techniques that are based on shallow network structures and are task specific. More recently, deep learning technique has been realized in the THz applications including metamaterial design, NDT, security inspection, material characterization and wireless communication systems. The THz applications deal with high dimension spatio-temporal data, as such deep learning methods have shown to outperform the simpler ML techniques in classification detection and related tasks. The deep learning approach provide increased system model performance, robustness and automatic, in-depth feature extraction relative to the conventional machine learning techniques and are thus significant for the optimization of THz system design and embedded data extraction and analysis. Accordingly, novel learning models have been introduced such as transfer learning, deep reinforcement learning, federated learning and broad learning systems. Frontiers in THz technology is advancing towards the biomedical application of THz technology as a potential emerging modality particularly, for the cancer cells imaging. The development of deep learning enabled THz cancer cells imaging systems will enable the development of computer aided detection and diagnosis systems for clinical decision support. Thus, we identify an existing limitation inhibiting the wide scale application of deep learning in the THz cancer applications. The suggested solutions will provide the roadmap for future research.

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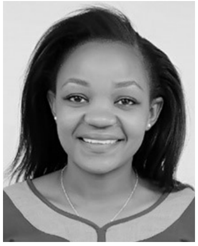

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