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SURVEY

Application of Infrared Thermography and Artificial Intelligence in Healthcare: A Systematic Review of Over a Decade (2013–2024)

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ABSTRACT Infrared thermography (IRT) is a non-invasive, radiation-free imaging technique that uses an infrared (IR) camera to record and produce an image using IR radiation emitted from the body. IRT imaging has shown promise as a screening method for breast cancer, diabetic foot ulcers, and dry eye disease, among other medical disorders. The aim of this systematic review is to present a complete overview of the applications of artificial intelligence (AI) techniques with IRT imaging for medical decision support systems over the course of the last ten years (2013–2024). Several scientific databases, including PubMed, IEEE, and Google Scholar, were searched using Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. After meeting the requirements for inclusion, 131 papers were selected. The reviewed studies demonstrated how various AI techniques, including deep learning and classical machine learning, can be used to develop automated diagnosis systems using IRT images. The efficacy of these AI systems differed depending on the medical field; for example, they could identify dry eye disease with 90–100% accuracy, classify diabetic foot ulcers with 85–95% accuracy, and detect breast cancer with 80–100% accuracy. This review highlights the value of IRT imaging in early disease detection, especially when combined with AI techniques. This work discusses challenges in using deep learning (DL) models in healthcare, including data scarcity and ethical considerations. It also, proposes three main recommendations: dataset standardization for ethical data management, clear governance models for ethical practices, and the use of Multimodal Large Language Models (MLLMs) to address explainability issues.

INDEX TERMS Infrared thermography, artificial intelligence, medical imaging, breast cancer detection, machine learning, deep learning, computer-aided diagnosis.

I. INTRODUCTION

Similar to established imaging technologies such as magnetic resonance, radiography, and ultrasound, infrared thermography (IRT) is one of the imaging modalities in healthcare. IRT

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is noninvasive, nonradiating, safe and suitable for all ages. It uses heat from the body to determine the temperature using an infrared (IR) camera to capture signs of abnormalities due to the increased temperature at the skin surfaces.

IRT has been widely adopted in many fields, such as medicine, manufacturing, construction, astronomy, automotive, aerospace and defect detection [1]. In the field of medicine alone, the medical applications of IRT are extensive. IRT encompasses two fundamental approaches: static and dynamic imaging techniques. Static imaging in IRT involves the capture of thermal data at a single time point, without any prior simulation and providing a snapshot of surface temperatures. In contrast, dynamic imaging in IRT involves the continuous monitoring and recording of thermal variations over time following the application of chemical, thermal, or mechanical stress [2].

Despite this, IRT is not the gold standard for various medical application areas. Like in the case of breast cancer screening, it is frequently seen as an adjunctive screening technique. Research findings indicate that IRT is not useful for screening for breast cancer; however, this may be because of the subjective interpretation made by medical professionals, leading them to conclude that using IRT images for diagnosis purposes is not a reliable method [3]. Thus, the use of IRT is concluded to be a supplementary tool for breast cancer screening [4]. This example demonstrated that there is a need for quality assurance by providing objective assessment when using IRT images as a screening technique. Otherwise, it could only be employed as a supplementary screening tool since it is deemed unreliable.

The use of artificial intelligence (AI) tools in medical imaging has significantly increased in recent years. The development of AI has strengthened the importance of IRT in medical imaging since AI-based algorithms are used to create medical decision support systems that help physicians identify patients. An IRT image is fed into the system and an output diagnosis is computed. It is an easy, fast, and objective diagnosis method. The incorporation of AI in medical diagnosis is a promising field and has initiated many works on automated decision support systems using IRT images. It is an ongoing active research area using AI and IRT in medicine. Lahiri et al. [5] provided a comprehensive review of the use of IRT in a range of medical applications a decade ago. Faust et al. [6] also investigated an extensive collection of AI-based algorithms employed to automatically analyze IRT images. They focused on describing technical details regarding these traditional machine learning (ML) algorithms used to develop a computer-aided diagnosis (CAD) system. Recently, due to the global COVID-19 pandemic, fever screening using IRT has been utilized worldwide for a quick and reliable initial diagnosis of the disease [7]. This has demonstrated the potential of this diagnostic modality in medicine.

IRT has shown promise in various medical applications, including ophthalmology. For instance, Figure 1 presents examples of infrared thermography images used in the diagnosis of dry eye disease. These images illustrate the temperature differences between healthy eyes and those affected by dry eye syndrome, demonstrating how IRT can visualize physiological changes associated with ocular surface disorders. Similarly, Figure 2 shows breast thermograms downloaded from the Database for Mastology Research (DMR) [8]. These images exemplify how IRT can be applied in breast cancer screening, highlighting temperature variations that may indicate the presence of abnormal tissue growth or increased vascularization associated with tumors.

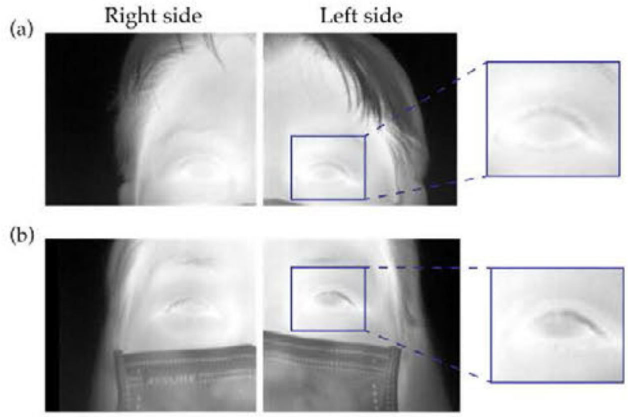

FIGURE 1. Examples of infrared thermography images of (a) an eye affected by dry eye disease and (b) healthy eye.

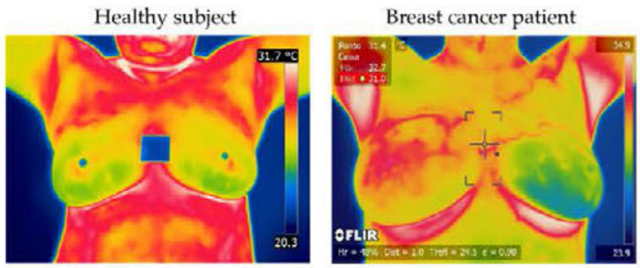

FIGURE 2. Breast thermograms from the Database for Mastology Research (DMR) [7] Left: thermogram of a healthy subject; Right: thermogram of a patient with pathological findings.

In their review article, He et al. [9] presented a comprehensive review focusing on the integration of infrared imaging-based machine vision with deep learning algorithms, emphasizing how this combination enhances automated decision-making across diverse fields, from medical diagnostics to remote sensing and quality control. Meanwhile, Magalhaes et al. [10] specifically examined the application of machine learning methods with IRT in medical diagnostics, though their scope is limited to traditional machine learning approaches. Despite the growing interest in the application of AI in medical imaging, there has been limited focus on its potential in conjunction with IRT. Previous reviews have explored the medical applications of IRT or the use of AI in IRT separately. However, to our knowledge, there has been no comprehensive systematic review that specifically investigates the integration of AI techniques with IRT across various medical domains. This systematic review aims to close this gap by providing a comprehensive overview of the scientific literature on the use of AI techniques, specifically

ML and DL, in conjunction with IRT for medical decision support systems. Our contributions are the following:

- We listed an extensive range of medical application areas employing IRT as an imaging modality.
- We presented a comprehensive literature of current AI-based techniques implemented in medical decision support systems using IRT as input data and their performances.
- We demonstrated the efficacy of IRT as a screening tool for various medical applications such as breast cancer and sports injury and so on.
- We discussed the shortcomings of current AI-based techniques and proposed appropriate mitigation approaches.
- We provided insights for the next steps towards a more reliable and trustworthy AI-based IRT as a clinical assistive tool.

The review paper is structured as follows: In Section II, background information regarding the origin of IRT is described. Then, the different medical application areas using IRT and AI-based algorithms following the search methodology are explained in Section III. Lastly, Section IV presents our findings and comments, including ideas for future study, and Section V concludes the paper.

II. BACKGROUND

Sir William Herschel's discovery of infrared radiation at the beginning of the 19th century was a substantial breakthrough in scientific knowledge. Still, significant progress in understanding its uses was accomplished in the late 1800s. Subsequent studies measuring infrared heat emitted by things, including the human body, were made possible by Herschel's discoveries. Subsequently, Hippocrates noted the importance of body temperature on health [11]. Similarly, Wunderlich made a substantial contribution to our understanding of body temperature as a pioneer in fever detection and its association with many disorders [11]. Over time, the basic relationship between body temperature and health disorders was established, providing the basis for the knowledge that little variations in body temperature may be signs of underlying health problems. This knowledge formed the basis for the development of IRT in modern medical diagnostics, which enables the use of IR cameras to detect abnormalities in images to support health evaluations.

Advanced infrared cameras and sophisticated image processing methods have made IRT a potent tool for noninvasive, real-time evaluation of a range of medical disorders. The potential of IRT imaging in modern healthcare settings has also been increased by the introduction of AI algorithms, which have created new possibilities for automated analysis and interpretation of IRT images.

III. SEARCH STRATEGY AND OUTCOME

This systematic review study was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a comprehensive and transparent selection of relevant articles on the application of thermography in human healthcare using AI. Only articles that were published between 2013 and 2024 were considered. The relevant articles were selected from the Institute of Electrical and Electronic Engineers (IEEE), Google Scholar, and PubMed scientific repositories. Specific Boolean search strings, including "Infrared thermography", "Machine Learning", "Deep Learning", and "Human Healthcare," were used in various combinations to identify articles focusing on machine learning and deep learning methods involving the application of thermography in healthcare. For instance, in the IEEE search database, the search strings "Infrared thermography" and "Machine Learning" or "Deep Learning" and "Human Healthcare" were chosen with filtering done to narrow the advanced search to full texts within the desired year range. In the PubMed search database, the search strings "Machine Learning" or "Deep Learning" and "Infrared thermography" were used and with the same filtering technique. Similarly, for the Google Scholar search database, the search strings "Infrared thermography", "Human Healthcare" and "Machine Learning" or "Deep Learning" were used, with keywords appearing anywhere in the article for the desired year range. The outcomes of the searches are shown in Table 1.

A. INCLUSION AND EXCLUSION CRITERIA OF THE STUDY

As shown in Table 1, 17 564 and 18 326 articles were initially identified using the Boolean search strings for machine learning and deep learning methods, respectively. The articles were screened based on the inclusion and exclusion criteria wherein around 17 206 irrelevant (theses, reviews, books) and 270 duplicate articles on machine learning and 17 833 irrelevant and 450 duplicate articles on deep learning were removed. Articles were included if they met the following criteria: (i) the articles were published before 2013; (ii) the articles were published in English; (iii) the articles discussed the use of IRT thermography in human healthcare. Articles that did not meet the inclusion criteria were excluded. The final selection yielded 88 articles for machine learning and 43 articles for deep learning, focusing on the application of infrared thermography in human healthcare. Figure 3 shows the PRISMA diagram.

B. MEDICAL DECISION SUPPORT SYSTEM

Medical decision support systems, computer-aided diagnosis (CAD) systems, have grown to be essential tools in assisting healthcare professionals. These systems leverage AI techniques to analyze medical data, including images, and provide objective assessments and recommendations. In the context of infrared thermography, medical decision support systems can automatically interpret thermal patterns and detect potential abnormalities, aiding in early diagnosis and treatment planning. The process of medical decision support systems typically consists of either machine learning (ML) algorithms

TABLE 1. Result of a Boolean search string on thermography using deep learning and machine learning methods in the healthcare industry.

Artificial Intelligence techniques	Scientific repositories	Title	AND [Title/Abstract/Full text]	No. of articles
Machine learning-based	IEEE, PubMed, Google Scholar	IEEE: "Infrared Thermography"	AND "Machine Learning" AND "Human Healthcare"	95
		PubMed: "Infrared thermography"	AND "Machine Learning"	69
		Google Scholar: "Infrared thermography in human healthcare using machine learning"	Any type of article	17,400
Deep learning-based	IEEE, Google Scholar, PubMed	IEEE: "Infrared Thermography"	AND "Deep Learning" AND "Human Healthcare"	88
		PubMed: "Infrared thermography"	AND "Deep Learning"	38
		Google Scholar: "Infrared thermography in human healthcare using deep learning"	Any type of article	18,200

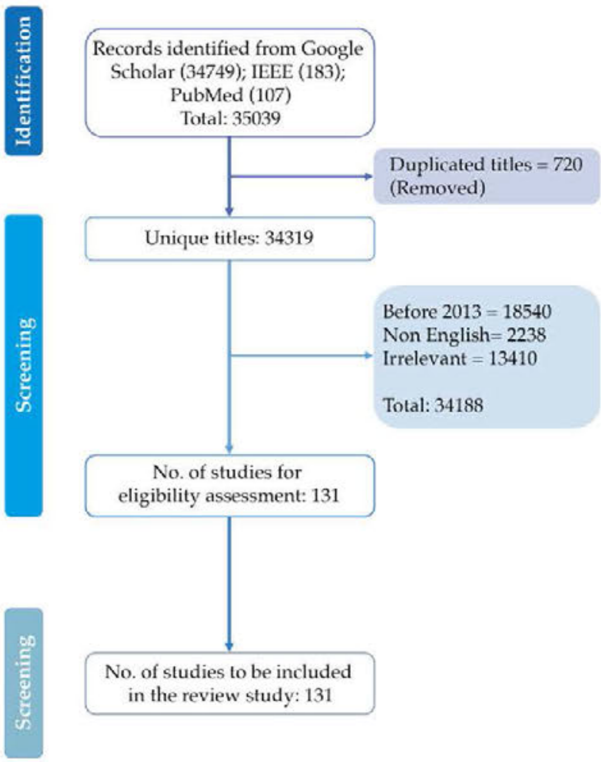

FIGURE 3. Inclusion of relevant articles based on PRISMA guidelines.

or deep learning (DL) techniques to analyze IRT images automatically.

1) TRADITIONAL MACHINE LEARNING

Traditional ML methods have been widely studied in the healthcare domain. For instance, Chandrasekar et al. [12] investigated the employment of neural network models to forecast the permeability of molecules through the placental blockade. The authors reported that the multi-layer perceptron model was the best-performing, yielding an accuracy of about 91%. Ansari et al. [13] explored machine learning models for permeability prediction of medicinal drugs across blood-brain blockades for neurological disease therapy. The authors reported that the tree-based ensemble models achieved the highest accuracy of about 96%.

Traditional ML relies on feature engineering whereby significant and distinctive features are extracted from the data with feature extraction techniques and are subjected to classifiers for automated characterization. It requires careful selection of hand-crafted features from the training data extracted using various feature extraction techniques and then feature ranking or selection techniques to select the highly distinctive features for classification. Contrast limited adaptive histogram equalization (CLAHE) [14] is a common pre-processing technique applied to IRT images to enhance the images before the feature extraction process.

Depending on the type of medical application area, certain data require segmentation before extracting distinctive features from the region of interest. Region growing technique, Otsu's thresholding, and lazy snapping are examples of segmentation techniques widely utilized in IRT images. Some of the common features extraction techniques commonly applied can be broadly grouped into the following:

- Wavelet-based techniques: discrete wavelet transform (DWT), double density dual tree complex wavelet transform, Gabor wavelet
- Texture-based techniques: gray-level run length matrix (GLRLM), gray-level co-occurrence matrices (GLCM), Gabor filter, speeded-up robust features (SURF), scale-invariant feature transform (SIFT)
- Statistical techniques: mean, skewness, kurtosis, energy, variance, entropy, cumulant features
- Nonlinear techniques: higher order spectra (HOS)
- Frequency-domain techniques: frequency and time domain features.

After extracting the features, it is a common practice to apply feature selection, ranking, or reduction techniques to reduce the number of features and to ensure that only the significant features are used for classification. Frequently utilized methods are singular value decomposition (SVD), and principal component analysis (PCA). Finally, the most common classifiers employed in IRT imaging include Naïve Bayes (NB), k-nearest neighbor (KNN), AdaBoost, random forest (RF), decision tree (DT), support vector machine (SVM), artificial neural network (ANN).

2) DEEP LEARNING

On the other hand, DL has the ability to self-learn from the pool of training data. Features engineering is not required. Convolutional neural network (CNN) is an example of a popular DL technique. Among CNN architectures, U-Net, VGG-16, ResNet50, DenseNet, and SqueezeNet are most employed. These models have gained popularity due to their architectures designed for tasks such as image classification, object detection, and segmentation. Specifically, pretrained models derived from extensive data and training offer a convenient approach for transfer learning, allowing users to leverage the learned features from a different but related task or dataset [15]. In some instances, robots are trained using deep learning algorithms for handling specific tasks such as environmental monitoring or post-disaster response [16]. Deep learning models are currently being fervently employed in healthcare.

Akhtar et al. [17] underscored the use of deep learning models to construct computer-aided software for the rapid identification of abnormalities or serve as a visualisation tool for hepatic resection. In another study, Ansari et al. [18] proposed the use of the unique Dense-Pyramid Scene Parsing-UNet deep model for the segmentation of liver ultrasound images. In their review study, Rai et al. described the effectiveness of employing image fusion and enhanced algorithms for thermal ablation tumour treatments. Ansari et al. [19] also accentuated the increased use of deep learning methods for ultrasound image segmentation of varying body regions for the diagnosis of medical conditions in another review study. Jung et al. [20] asserted that the use of AI results in high diagnostic accuracies for fracture cases, underscoring the possible use of AI for fracture diagnosis in healthcare. Quite similarly, Luan et al. [21] reported that the use of the novel adaptive matching network improved the localization accuracy of microvessel imaging.

3) MEDICAL APPLICATION AREAS

The literature reviews presented in Tables 4 and 5 showcase a variety of medical applications for ML and DL techniques using IRT images. We have categorized the medical application areas using ML techniques into the following categories (in alphabetical order):

- Cardiovascular health: this category encompasses cardiovascular disease diagnosis, heart rate variability parameter estimation using facial images, hemodynamic shock prediction, hypertension detection, and blood pressure measurement.
- Mental health: applications in this area include expression recognition, schizophrenia severity assessment, and stress detection.
- Metabolic conditions: this category includes childhood obesity identification, foot temperature pattern analysis for diabetes mellitus identification, diabetic foot ulcer detection, and tongue thermography for diabetes classification.
- Musculoskeletal health: this area covers arthritis and rheumatoid conditions, lumbosacral radiculopathy classification, handgrip exercise assessment, posture and spinal curvature analysis for back pain, and bone fracture analysis.
- Ophthalmological conditions: studies in this category focus on dry eye and meibomian gland dysfunction detection and classification.
- Other health conditions: this diverse category ranges from cellulite staging to fever screening and thyroid condition detection.
- Respiratory health: this area involves breathing analysis, pneumonia detection, and COVID-19 classification using thermal imaging.
- Skin health and dermatology: studies in this category focus on burn wound analysis, skin disease detection, skin neoplasm classification, and melanoma identification.
- Tumor detection: studies in this category primarily focus on breast cancer detection and classification, with some research on brain tumor analysis.

Similarly, from the contents recorded in Table 5, we categorized the following medical application areas using DL techniques:

- Cardiovascular health: this area includes hypoperfusion severity classification in critically ill patients using leg thermogram images and DL models.
- Metabolic conditions: this category includes diabetes mellitus identification using foot and tongue images. Studies have applied deep learning techniques to analyze plantar thermal images and tongue thermograms for diabetes detection.
- Musculoskeletal health: studies in this category have investigated the use of infrared imaging and DL for bone trauma analysis, particularly in cases of suspected bone fractures.
- Respiratory health: DL techniques have been applied to analyse CT images for COVID-19 lesion detection and classification.
- Skin health and dermatology: DL models have been used to analyze skin images, combining visual and thermal information for various skin condition classifications.
- Tumor detection: this category remains the primary focus of DL applications in IRT imaging, with a strong emphasis on breast cancer detection. Studies in this area include breast cancer classification, segmentation, and feature extraction using various DL architectures.

IV. DISCUSSION

Over the past ten years, there has been an increasing trend in the use of AI techniques in conjunction with IR thermography for medical research (Figure 4). The number of studies that have used both ML and DL techniques for IR image analysis has been steadily rising since 2013. Traditional ML techniques dominated the first few years (2013-2017), while no DL studies were published during the same period. On the other hand, DL applications saw a significant increase starting in 2018 and continued in line with ML research. Research activity reached its peak between 2019 and 2022, with a particularly notable spike in DL studies during this time. This pattern reflects the quick development of AI and the increasing awareness of IR thermography's potential in medical diagnostics.

A. AI RESEARCH FOR IRT IMAGING

The literature tables (Tables 4 and 5) present a comprehensive review of studies utilizing IRT images and AI techniques in various medical domains. These studies highlight the growing interest and potential of integrating IRT with AI for diagnostic and screening purposes. The tables summarize key information, including dataset characteristics, the specific AI techniques, and performance metrics.

1) ML APPROACHES

According to Table 4, there are 9 broad medical application areas, namely tumor detection (primarily focused on breast cancer), cardiovascular health, mental health, metabolic conditions, musculoskeletal health, ophthalmological conditions, respiratory health, skin health and dermatology, and other health conditions. Across these various medical research areas, a diverse range of 88 studies has been conducted. Breast cancer detection emerged as the most extensively studied application area, with 40 studies focusing on this domain. This high interest can be attributed to the potential of IRT as a non-invasive and radiation-free alternative to traditional mammography. Other areas, such as diabetic foot ulcer assessment and dry eye disease diagnosis, also received notable attention, highlighting the versatility of IRT in detecting various physiological abnormalities. However, some application areas, such as mental and respiratory health, had relatively fewer studies, indicating potential opportunities for further exploration. Figure 5 depicts the number of studies conducted on varying diseases using IR thermography and ML methods. From the figure, it is apparent that breast cancer is being most widely studied using IR thermography in comparison to other diseases.

The use of ML to IR thermography has demonstrated promising results across different medical domains. Table 2 summarizes the top-performing studies using traditional ML techniques across various medical applications of IRT. These studies share common characteristics such as sophisticated feature extraction methods, model selection among different classifiers, and often, the use of domain-specific knowledge to guide the analysis. The performance achieved by studies demonstrates the effectiveness of classical ML approaches in analyzing thermal images for diagnostic purposes. Specifically, in tumor detection, particularly breast cancer, numerous studies have reported high accuracies, with some achieving up to 100% accuracy using advanced techniques like temperature time series analysis [22] and singular value decomposition [23]. Cardiovascular health applications have shown moderate success, with accuracies around 89% for hypertension diagnosis [24] and 73% for hemodynamic shock prediction [25]. Mental health research, though less explored, has demonstrated potential in stress detection [26] and expression recognition [27], with accuracies ranging from 78% to 85%.

TABLE 2. Number of ML studies conducted in each category along with the best accuracy achieved. Note that for musculoskeletal health, the best performance is reported in terms of sensitivity.

Category	Number of studies	Best Accuracy	Reference
Tumor Detection	40	100%	Silva et al., 2016 [22], Ali et al., 2015 [36], Gaber et al., 2015 [37]
Cardiovascular Health	5	90%	Jayanthi and Anburajan 2019 [38]
Mental Health	3	94.3%	Jian et al., 2017 [39]
Metabolic Conditions	8	98.0%	Rashmi et al., 2021 [40]
Musculoskeletal Health	4	83%	Umapathy et al., 2017 [30]
Ophthalmological Conditions	8	100%	Celik et al., 2013 [41]
Respiratory Health	3	100%	Prochazka et al., 2017 [32]
Skin Health and Dermatology	7	85.3%	Martinez-Jimenez et al., 2018 [33]
Other Health Conditions	10	98%	Gopinath and Prabu, 2016 [35]

In metabolic conditions, diabetic foot assessment has been a key focus, with studies reporting accuracies above 90% in detecting complications [28]. Musculoskeletal health applications have shown good results in detecting postural issues [29] and rheumatoid arthritis [30], with accuracies ranging from 83% to 90%. Ophthalmological conditions, particularly dry eye disease, have seen some of the highest accuracies, often exceeding 99% [31]. While respiratory health applications are less common, the few studies conducted show promising results, such as 100% accuracy in detecting facial temperature changes related to breathing disorders [32]. Skin health and dermatology applications have demonstrated good potential in burn wound analysis [33] and skin neoplasm classification [2], with accuracies of around 85%. Other health conditions, such as cellulite staging [34] and thyroid abnormality detection [35], have also shown encouraging results with accuracies of 80.9% and 98% respectively. These findings underscore the value of IR thermography for medical applications, with particularly strong performance in breast cancer detection and ophthalmological conditions.

2) DL APPROACHES

Table 5 lists the six primary medical application areas of DL in combination with IRT imaging: tumor detection (with a predominant focus on breast cancer), cardiovascular and metabolic conditions, musculoskeletal and respiratory health, and skin and dermatology. Table 3 presents an overview of the highest-performing studies that employed DL techniques for analyzing IRT images in various medical contexts. It's noteworthy that many of these high-performing DL studies utilize transfer learning, leveraging pre-trained models on large datasets and fine-tuning them for specific thermal imaging tasks. This approach appears particularly effective

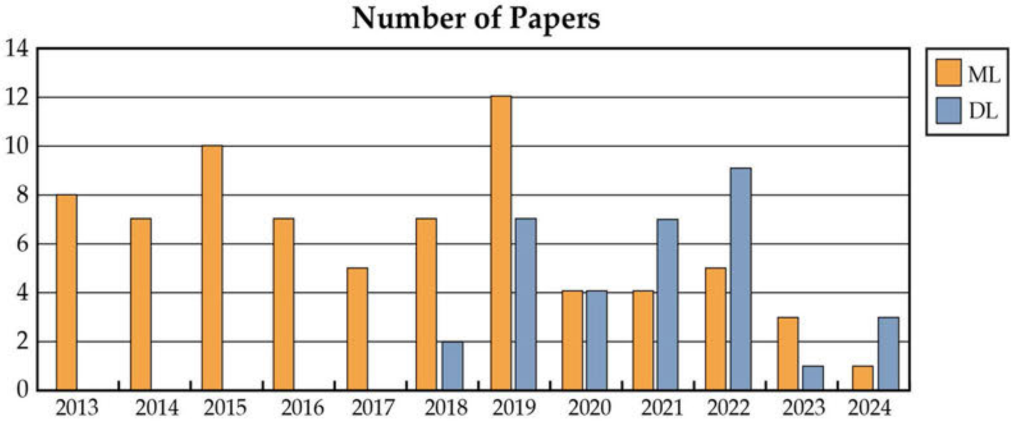

FIGURE 4. Number of studies on deep learning versus machine learning techniques with IR thermography, between 2013-2024.

TABLE 3. Number of DL studies conducted in each category along with the best accuracy achieved.

Category	Number of studies	Best Accuracy	Reference
Tumor Detection	34	100%	Al Husaini et al., 2021 [42]
Cardiovascular Health	1	94%	Luo et al., 2023 [43]
Metabolic Conditions	3	94.2%	Thirunavukkarasu et al., 2019 [44]
Musculoskeletal Health	1	N/A	Der Strasse et al., 2022 [45]
Respiratory Health	1	98.4%	Jingxin et al., 2022 [46]
Skin Health and Dermatology	1	96.4%	She et al., 2024 [47]
Fever	1	97.0%	Da Silva et al., 2022 [48]
Eye disease	1	97.0%	Madura et al., 2021 [49]

given the often limited size of medical thermal imaging datasets.

A total of 43 studies using DL techniques have been carried out in these medical research areas. With 34 of the 43 studies concentrating on this domain, breast cancer detection was found to be the most common application area. Much less research has been done in other areas, such as the identification of diabetes mellitus and the classification of hypoperfusion severity. The limited diversity in application areas for DL studies compared to ML studies suggest significant opportunities for expanding DL applications in IRT to other medical domains. Figure 6 illustrates the distribution of DL studies across different diseases using IR thermography. The figure shows that, compared to all other areas of investigation, breast cancer detection is by far the most researched application of DL in IRT.

DL applications in infrared thermography have shown promising results, albeit with a strong focus on specific areas. Numerous studies have reported high accuracies in tumor detection, particularly breast cancer. For example, Ekici and Jawzal [50] used a CNN model in combination with image statistics and biodata to reach an impressive accuracy of 98.9%. In a similar work, Mohamed et al. [51] demonstrated binary categorization of breast thermograms with 99.3% accuracy using a CNN. Sánchez-Cauce et al. [52] showed the potential of multi-input models by combining thermal pictures with personal and clinical data. Using this multimodal approach, the authors obtained 97% accuracy. In the field of metabolic disorders, Thirunavukkarasu et al. [44] classified diabetes from tongue thermograms using CNN and obtained 94.2% accuracy. Cruz-Vega et al. [53] reported 85.3% accuracy using a deep model for diabetic foot thermogram categorization. Cardiovascular health applications have not received as much attention, but they have potential. Luo et al. [43] used a ResNet model on leg thermograms to diagnose hypoperfusion severity in critically sick patients with 94% accuracy. Der Strasse et al. [45] explored the use of infrared pictures for bone trauma diagnosis in the musculoskeletal health domain, demonstrating the promise of DL in this field. Jingxin et al. [46] provided an example of respiratory health applications, reporting a mean accuracy of 98.4% in COVID-19 lesion identification and classification using CT scans and a ResNet 50 model. She et al. [47] combined visual and thermal data with a DenseNet model to obtain an identification rate of 96.4% for a variety of skin disorders in the field of dermatology and skin health. These results highlight the promise of DL in the analysis of IR thermography for a range of medical applications. However, the heavy concentration of studies in breast cancer detection also highlights the need for more diverse applications of these techniques in the field of IRT imaging.

B. COMPARISON BETWEEN ML AND DL APPROACHES

Some similarities between ML and DL techniques could be drawn from the studies in Tables 4 and 5. It is evident that where IRT is concerned, both methods exhibit the potential to pre-process thermal images, detect patterns and extract expedient features from the images, identify abnormalities and forecast results. Furthermore,

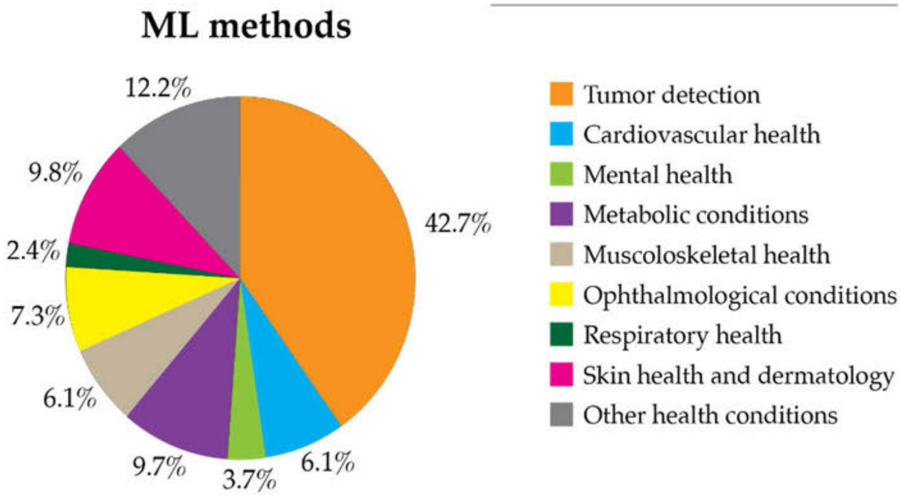

FIGURE 5. Number of studies conducted on disparate diseases using machine learning techniques with IR thermography.

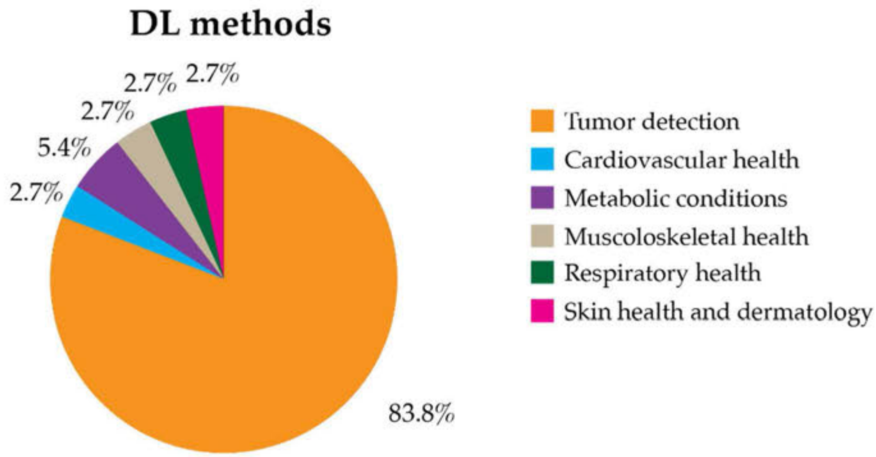

FIGURE 6. Number of studies conducted on different diseases using deep learning techniques with IR thermography.

both methods require the training and validating IRT data on unseen data using techniques such as cross-validation [54] for the accurate classification of thermal images.

Contrastingly, while ML involves a laborious task, comprising the manual extraction of features from thermal images by experts, DL involves the automatic extraction of features from the images due to the presence of filters in the convolution layers of models such as the convolutional neural networks [55]. Additionally, while ML approaches require only small IRT datasets to perform well, DL approaches require large datasets for effective training and classification of data. Furthermore, DL models have the potential to capture complex patterns in the IRT data for the extraction of distinct features due to the presence of multi layers, hence resulting in higher classification accuracies as compared to conventional ML models [56], making DL methods exceptionally suitable for high-resolution IRT image analysis that requires more superior feature detection.

C. CURRENT CHALLENGES, LIMITATIONS AND FUTURE DIRECTIONS

Several studies highlighted the significance of CAD tools in enhancing the processing and diagnostic accuracy of IRT images. Overall, the diversity in methodologies and model performances underscores the ongoing advancements and potential in leveraging IRT imaging for breast cancer detection. However, IRT as an imaging modality has limitations. Its functional-based nature, as opposed to established structural imaging modalities such as X-ray and MRI, makes it more challenging to directly correlate IRT findings with specific anatomical issues and known diseases or conditions [11].

Several factors make the application of AI to IRT challenging. Training successful AI systems requires access to large and diverse datasets. However, the current challenge of data scarcity presents difficulties in the training of DL models, resulting in the dismissal of the use of such models [55]. Also, in the medical domain, privacy issues frequently hinder the sharing and access of patient data, limiting the creation of precise and trustworthy medical decision support systems. Hence undoubtedly, ethical considerations are becoming largely imperative to data science practices. The ethical setting in data science is influenced by technological advancements alongside cultural and societal contexts in which data is collected and studied [57]. This is especially so in the healthcare domain, which comprises sensitive data that necessitates a high level of ethics [57]. Thus, the future direction calls for the standardization of datasets for ethical data management wherein the assurance of interoperability and accessibility practices enable the facilitation of ethical data sharing and collection, imperative for enhancing scientific knowledge, all while protecting individual rights and privacy [57]. Additionally, Georgieva et al. [58] concur on the need for clear governance models that underscore responsibility and influence the implementation of ethical practices in data science. Thus, there is a need for data scientists to address privacy and agreement, power inequities and the effect of data on minority populations as these ethical challenges are bound to become more intricate, requiring ongoing debate, research and acclimatization to ensure that data science practices are parallel to ethical practices and societal values, as data science continues to evolve [57].

The lack of explainability, especially when using DL techniques to develop medical decision support systems also poses another challenge in the employment of DL models. In medical applications such as diagnostic support systems or CAD systems, understanding why a particular decision is made is critical for gaining trust and acceptance from healthcare professionals. Thus, the lack of explainability in these AI systems can be a significant barrier to their clinical deployment. Such a barrier could be mitigated through the use of Multimodal Large Language Models (MLLMs), which have the potential to be incorporated into thermal images [59]. Temperature variations captured by the thermal images through the use of heat maps combined with the potential of MLLMs to leverage pre-trained models for the extraction of features all underscore how the DL models could explain features responsible for the decisions made by the model, hence mitigating barriers through this emanating research direction in IRT.

The literature review also highlights the need for standardized evaluation metrics and reporting guidelines in AI-based IRT studies. While accuracy was the most reported performance metric, some studies also included sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). However, the inconsistent reporting of these metrics across studies makes it challenging to directly compare the performance of different AI techniques and IRT systems. Establishing standardized evaluation protocols and reporting guidelines would facilitate better comparison and reproducibility of results across different studies.

Hence, overcoming these challenges might involve the following aspects:

- Data collaboration: creation of shared repositories where researchers can access a diverse pool of IRT images. This collaborative approach is essential for creating large datasets and developing robust AI models that can handle the complexities of real-world medical data.
- Multimodal data: combining data from various sources has shown to be incredibly beneficial in building more accurate AI models [60]. Future research should focus on integrating IRT images with other imaging modalities (like MRI or CT scans) and relevant clinical data (such as patient history or lab results). Studies have demonstrated that this multimodal approach can significantly enhance the performance of AI systems in medical applications, particularly in areas like breast cancer detection and skin condition diagnosis [50], [52].
- Explainable and transparent models: development of strategies to make AI models more understandable to healthcare professionals. This involves incorporating methods to quantify uncertainty [61] and implementing explainable AI techniques [62]. Tools like saliency maps, attention mechanisms, and rule-based explanations can offer valuable insights into how AI models perform image classification.
- Standardization of data acquisition and preprocessing: development of consistent protocols for IRT image capture, including specifications for camera equipment, imaging conditions, and patient preparation. This standardization is key to reducing variability between studies and increasing the reproducibility of the findings in AI-based IRT research.

V. CONCLUSION

This review has shown that IRT is a feasible modality by providing an in-depth overview of previous studies that combine this imaging technique with AI in the medical field. This work is novel as it discusses the current challenges pertaining to the use of DL models in healthcare applications due to data scarcity and ethical considerations and thereafter, proposes three main recommendations for the successful use of DL models in healthcare in the future; (i) the need for the standardization of dataset for ethical data management hence promoting ethical data sharing while preserving the rights and privacy of individuals, (ii) the need for the employment of clear governance models that underscore responsibility and influence the implementation of ethical practices in data science, (iii) the use of MLLMs to circumvent barriers to the clinical deployment of AI systems due to explainability issues.

Our analysis also highlights the evolution from traditional ML approaches to more sophisticated DL models, revealing significant improvements in accuracy and performance across various medical applications. The ability of these AI systems to process and interpret complex thermal patterns has opened new avenues for noninvasive, radiation-free diagnostic tools.

APPENDIX

See Tables 4 and 5.

TABLE 4. Summary of studies that applied infrared thermography in healthcare applications using ML approaches.

Author, year	Application	Participant/data information	Features and methods	Findings/Results (%)
EtehadTavakol et al., 2013 [63]	Tumor detection	9 malignant, 12 benign, 11 healthy breast images	Implemented breast thermogram image segmentation using fuzzy c-means clustering technique. Extracted bispectral invariant features from Radon projections, followed by selection and fusion of top features using Adaboost classifier.	Accuracy: 95.0
Celik et al., 2013 [41]	Ophthalmological conditions	29 dry eye and 26 healthy eye thermogram images	Gland segmentation from thermogram images of dry eye using Gabor wavelets. Extraction of gland and inter-gland features. Classification using SVM.	Accuracy: 100.0
Krawczyk and Schaefer 2013 [64]	Tumor detection	29 malignant, 117 benign breast images	Extraction of characteristics from breast thermogram image areas that characterize bilateral differences. Ensemble classifier and extension of Under-Sampling Balanced Ensemble algorithm.	Accuracy: 88.7; Sensitivity: 81.3; Specificity: 95.5
Krawczyk and Schaefer 2013 [65]	Tumor detection	29 malignant, 117 benign breast images	Breast thermogram images. Ensemble of one-class classifiers. Diversity measure to select members of committee	Accuracy: 87.4; Sensitivity: 82.1; Specificity: 88.7
Nicandro et al., 2013 [66]	Tumor detection	77 malignant, 21 healthy breast images	Bayesian network classifiers with Hill-Climber scoring algorithm and 10-fold cross validation.	Bayesian networks: Accuracy: 71.8; Sensitivity: 82.0; Specificity: 37.0
Peregrina-Barreto et al., 2013 [67]	Metabolic conditions	Diabetes mellitus type 2 patients with and without neuropathy	Estimated temperature differences in diabetic feet using a hot spot estimator. Developed a method for detecting ulceration risks in diabetes mellitus type 2 patients with and without neuropathy.	Proposed method reliably assists specialists in early detection of ulceration risks in diabetic foot
Oe et al., 2013 [68]	Metabolic conditions	18 diabetic patients with 20 occurrences of diabetic foot	Analyzed range of increased skin temperature using Fisher's exact test. Examined morphological patterns of temperature distribution in diabetic foot cases.	High positive predictive value of 100
Chan et al., 2013 [69]	Other health conditions	1517 patients with or without fever	Compared infrared thermography with traditional thermometry methods using AUC-ROC. Analyzed frontal and lateral thermographic views.	The use of remote forehead infrared thermography readings for fever screening should be abolished.
Sella et al., 2013 [70]	Tumor detection	256 healthy subjects, 178 breast cancer patients	Employed multiparametric computer analysis with a three-dimensional infrared imaging system. Analyzed metabolic signatures from breast lesions using AUC-ROC.	AUC-ROC: 86
Arita et al., 2013 [71]	Ophthalmological conditions	16 eye images from 16 healthy subjects, 19 eye images from 19 patients with Meibomian gland dysfunction	Examined correlation between surface temperature and ocular surface features using ocular symptom, eyelid margin, superficial punctate keratopathy, and meibum scores. Applied Mann-Whitney U test and Spearman rank correlation test for analysis.	Measured scores were largely higher in patients with Meibomian gland dysfunction compared to healthy subjects
Araujo et al., 2014 [72]	Tumor detection	14 malignant, 19 benign and 21 cyst breast images	Utilized Euclidean distance and symbolic data analysis. Extracted four interval variables from morphological and thermal matrices, along with continuous features. Applied Fisher's criterion to transform extracted features.	Accuracy: 84.0; Sensitivity: 85.7; Specificity: 86.5
Francis et al., 2014 [73]	Tumor detection	11 abnormal, 11 normal breast images	In the multiresolution curvelet area, statistical and textural features were extracted from thermograms. Employed SVM classifier for analysis.	Accuracy: 90.9; Sensitivity: 81.8; Specificity: 100.0
Francis et al., 2014 [74]	Tumor detection	12 malignant, 24 normal breast images	Extracted texture features from rotational thermogram series. Applied SVM classifier for analysis.	Accuracy: 83.3
Krawczyk and Schaefer 2014 [75]	Tumor detection	29 malignant, 117 benign breast images	Developed an ensemble classifier using neural networks and SVM as base classifiers. Incorporated a neural fuser to add classifiers and a fuzzy measure to evaluate ensemble diversity.	Accuracy: 89.0; Sensitivity: 81.9; Specificity: 90.8

TABLE 4. *(Continued.)* Summary of studies that applied infrared thermography in healthcare applications using ML approaches.

Marina et al., 2014 [76]	Tumor detection	14 abnormal, 26 normal breast images	Utilized gray level co-occurrence matrices for feature extraction. Applied SVM, Naïve Bayes, and KNN classifiers with 5-fold cross validation. Performed receiver operating characteristic analysis.	Accuracy: 92.0; Sensitivity: 78.6; Specificity: 100.0
Acharya et al., 2014 [31]	Ophthalmological conditions	40 responded, 41 not responded dry eye images	Analyzed clinical parameters (Schirmer's test, corneal staining, tear break up time) to classify thermograms. Extracted features including mean, entropies, kurtosis, skewness, and energy from thermograms. Ranked features based on t values and applied various classifiers.	KNN classifier: Accuracy: 99.8; Sensitivity: 99.7; Specificity: 100.0
Rassiwala et al., 2014 [77]	Tumor detection	1008 female participants	Comparison of breast thermograms using temperature gradient	Sensitivity: 97.6; Specificity: 99.2; Positive predictive: 83.7
Koprowski 2015 [29]	Musculoskeletal health	300 healthy, 200 faulty postures and 500 lateral spinal curvature back pain images	Identified external body contours and recognized arm, hip, and shoulder positions. Applied mesh and analyzed paraspinal muscles. Utilized SVM, DT classifiers, and neural networks.	SVM classifier: Sensitivity: 90.0; Specificity: 88.0
Ali et al., 2015 [36]	Tumor detection	34 malignant, 29 healthy breast images	Extracted texture and statistical features from regions of interest in breast thermograms. Applied SVM classifier with kernel function.	Accuracy: 100.0
Gaber et al., 2015 [37]	Tumor detection	34 malignant, 29 healthy breast images	Implemented optimized Fast Fuzzy c-mean algorithm with Neutrosophic sets for breast thermogram image segmentation. Evaluated using precision, recall, and accuracy metrics. Applied SVM classifier.	Accuracy: 100.0
Mejia et al., 2015 [78]	Tumor detection	9 abnormal, 9 normal breast images	Conducted textural analysis based on statistical measures. Extracted features from breast thermograms' regions of interest. Applied KNN classifier.	Accuracy: 99.4
Milosevic et al., 2015 [79]	Tumor detection	13 abnormal, 37 normal breast images	Extracted 20 textural features from gray-level co-occurrence of breast mammogram image regions of interest. Applied KNN, Naïve Bayes, and SVM classifiers with 5-fold cross validation.	SVM classifier: Accuracy: 88.0; Sensitivity: 76.9; Specificity: 91.9
Pramanik et al., 2015 [80]	Tumor detection	123 unhealthy, 183 healthy breast images	Applied discrete wavelets transform and extracted features from initial feature point images. Utilized artificial neural network for classification.	Accuracy: 90.4 Sensitivity: 87.6; Specificity: 89.7
Silva et al., 2015 [81]	Tumor detection	11 abnormal, 11 normal breast images	Computed features from thermal regions and applied KNN classifier. Assessed clustering using Calinski-Harabasz index, Davies-Bouldin index, and silhouette index.	Accuracy: 90.9; Sensitivity: 81.8; Specificity: 100.0
Wahab et al., 2015 [82]	Tumor detection	240 breast images	Extracted multiple features from different types of breast tissue for tumor localization. Utilized neural network for classification.	Accuracy: 92.8
Hernandez-Contreras et al., 2015 [83]	Metabolic conditions	30 non-diabetic, 30 diabetic foot images	Employed 3-dimensional morphological pattern spectrum and relative position to identify patterns in thermographic images of diabetic foot. Applied neural network for classification.	Accuracy: 94.3; Sensitivity: 97.3; Specificity: 91.3
Acharya et al., 2015 [84]	Ophthalmological conditions	83 dry eye, 21 healthy images	Extracted nonlinear Higher Order Spectra features and ranked them using t-test. Applied conventional classifiers including KNN, Naïve Bayesian, DT, Probabilistic neural network, and SVM.	KNN classifier: Accuracy: 99.8; Sensitivity: 99.8; Specificity: 99.8
Lashkari et al., 2016 [85]	Tumor detection	67 breast images	Extracted 23 features, including gray-level co-occurrence matrix, histogram, morphological, and statistical. Applied various feature selection methods. Utilized conventional classifiers including Adaboost, SVM, Naïve Bayes, and KNN.	Adaboost classifier: Accuracy: 87.4

TABLE 4. *(Continued.)* Summary of studies that applied infrared thermography in healthcare applications using ML approaches.

Raghavendra et al., 2016 [86]	Tumor detection	25 malignant, 25 normal breast images	Utilized histogram of oriented gradients and kernel locality preserving projection to reduce dimension of extracted descriptors. Applied conventional classifiers and developed a breast cancer risk index.	DT classifier: Accuracy: 98.0; Sensitivity: 96.6; Specificity: 100.0
Sathish et al., 2016 [87]	Tumor detection	40 abnormal, 40 normal breast images	Analyzed shape features using polynomial curve fitting. Extracted histogram and gray level co-occurrence matrix-based texture features from segmented images. Applied SVM classifier.	SVM with radial basis function: Accuracy: 90.0; Sensitivity: 87.5; Specificity: 92.5
Silva et al., 2016 [22]	Tumor detection	40 abnormal, 40 normal breast images	Segmented breast regions and built temperature time series. Applied 39 conventional classification algorithms.	Accuracy: 100.0; Sensitivity: 100.0; Specificity: 100.0
Zadeh et al., 2016 [88]	Tumor detection	Breast tissue disease images from 60 patients	Used fuzzy active contours to extract abnormal breast regions. Estimated Hausdorff and mean distance between normal and automated method.	Accuracy: 91.8; Sensitivity: 85.0
Gopinath and Prabu 2016 [35]	Other health conditions	30 abnormal, 21 normal thyroid neck images	Preprocessed images using median filter and segmented using Otsu's technique. Extracted features using Gabor filter and gray level co-occurrence matrix. Applied DT classifier.	Accuracy: 98.0; Sensitivity: 95.0; Specificity: 99.0
Lessa and Marengoni 2016 [89]	Tumor detection	46 abnormal, 48 normal breast images	Segmented regions of interest and extracted eight statistical features. Applied artificial neural network for classification.	Accuracy: 85.0; Sensitivity: 87.0; Specificity: 83.0
Glowacz and Glowacz 2016 [90]	Finger skin detection	3 different types of finger images	RGB colour space analysis, image histogram, binarization, averaging filter, KNN classifier	Proposed method is useful in diagnosing pathologies of human skin.
Liu et al., 2016 [91]	Facial nerve function	390 facial thermal images	Division of facial infrared images into 8 regions based on temperature, radial basis function neural network	Accuracy: 94.1
Yamaguchi et al., 2016 [92]	Dry eye	94 eyes from participants without lid diseases or conjunctivochalasis	Correlation of corneal temperature with tear file breakup time, receiver operating characteristic curve	Sensitivity: 83.0; Specificity: 80.0
Prochazka et al., 2017 [32]	Respiratory health	1 subject (25 experiments)	Detected facial parts with temperature changes for breathing disorders. Analyzed video sequences using digital filters and spectral estimation for assessing depth matrices. Applied artificial neural network.	Accuracy: 100.0
Sudarshan et al., 2017 [93]	Ophthalmological conditions	Thermogram eye images from 42 healthy subjects and 42 dry eye patients	Extracted higher order spectra and cumulant features. Applied conventional classifiers for analysis.	Accuracy: 90.5
Sudharsan et al., 2017 [94]	Ophthalmological conditions	Thermogram eye images from 21 healthy subjects and 83 dry eye patients	Applied discrete wavelet and Gabor transform. Used PCA for dimension reduction and a SVM classifier.	Accuracy: 97.0
Araujo et al., 2017 [95]	Tumor detection	78 malignant, 66 benign, 100 normal breast images	Transformed infrared breast images to grayscale and segmented to obtain regions of interest. Applied SVM classifier with radial function kernel. Used 4-fold cross validation for database 1 and holdout technique for database 2.	Accuracy: 94.8
Thiruvengadam and Mariamichael 2017 [24]	Cardiovascular health	14 hypertensive, 14 normal images	Analyzed static and dynamic infrared thermogram images of skin areas. Computed average skin temperature from static thermograms and statistical features from dynamic thermograms. Applied feature selection based on PCA and used artificial neural network.	Accuracy: 89.0; Sensitivity: 85.7: Specificity: 92.9
Jian et al., 2017 [39]	Mental health	18 moderately and 17 significantly ill schizophrenia images	Analyzed facial temperature changes based on varying emotions. Applied dimensionality reduction using multivariate analysis of variance and component analysis. Utilized SVM classifier.	Accuracy: 94.3

TABLE 4. *(Continued.)* Summary of studies that applied infrared thermography in healthcare applications using ML approaches.

Martinez-Jim et al., 2018 [33]	Skin health and dermatology	34 patients for training and 22 patients for validation	Analyzed temperature differences between injured and healthy skin for burn wounds. Applied random forest classifier, receiver-operating characteristic curve, and k-means clustering.	Accuracy: 85.3
Samant and Agarwal 2018 [96]	Diabetes detection using iris	180 diabetic patients, 159 healthy subjects	Extraction of statistical, textural and discrete wavelet transform features, t-test for feature selection, six machine learning classifiers	RF classifier: Accuracy: 89.6; Sensitivity: 98.8; Specificity: 96.9
Morales-Cervantes et al., 2018 [97]	Tumor detection	206 breast thermograms	Computation of thermal asymmetries, thermal scores linked to abnormality	Sensitivity: 100.0; Specificity: 68.7. Positive predictive: 11.4
Umapathy et al 2018 [30]	Rheumatoid arthritis	30 patients, 30 healthy subjects	Extraction of statistical features, K means and fuzzy algorithm, ROC curve	Sensitivity: 86.6; Specificity: 79.0
Wang et al., 2018 [27]	Mental health	3561 facial images (2124 positive, 1437 negative) from 22 subjects	Learned feature representations from visible and thermal images. Applied support vector machine classifier to classify paired and unpaired facial images. Utilized artificial neural network for analysis.	Accuracy: 85.5
Adam et al., 2018 [28]	Metabolic conditions	107 foot images from 66 diabetic patients and 51 healthy subjects	Decomposed foot thermograms using double density-dual tree-complex wavelet transform. Extracted entropy and texture features from decomposed foot images. Applied KNN classifier.	Accuracy: 93.1; Sensitivity: 90.3; Specificity: 98.0
Gogoi et al., 2018 [23]	Tumor detection	117 abnormal, 290 normal breast images	Utilized singular value decomposition to characterize breast thermal patches. Applied SVM classifier with polynomial kernel and ten-fold cross validation.	Accuracy: 98.0; Sensitivity: 98.0; Specificity: 98.0
Magalhaes et al., 2018 [98]	Skin health and dermatology	68 malignant, 17 benign skin images	Performed statistical computations on skin neoplasms. Obtained average temperature profile by groups and types of skin tumour. Applied conventional classifiers.	KNN classifier: Accuracy: 60.0
Santana et al., 2018 [99]	Tumor detection	219 cysts, 371 benign, 235 malignant breast images	Extracted geometry and texture features using Zernike and Haralick moments. Evaluated proposed system using Kappa index and accuracy. Applied ensemble classifiers.	Accuracy: 73.3; Sensitivity: 78.0; Specificity: 88.0
Khan and Arora 2018 [100]	Tumor detection	35 abnormal, 35 normal breast images	Extracted texture features using Gabor filters. Classified thermograms into normal and cancerous based on textural asymmetry. Applied support vector machine classifier.	Accuracy: 84.5
Silva et al., 2019 [101]	Musculoskeletal health	1365 forearm thermographic images from 13 participants	Analyzed three regions of interest from forearm thermograms during handgrip exercise. Extracted average temperature and standard deviation from regions of interest. Implemented Matlab-based analysis.	Proposed Matlab-based analysis yielded superior results compared to standard tool provided by camera manufacturer
Vardasca et al 2019 [102]	Diabetic foot ulcer	56 patients with diabetic foot ulcer	Extraction of thermal features (mean, median, standard deviation) from regions of interest, k-nearest neighbour.	Accuracy: 92.5
Jayanthi and Anburajan 2019 [38]	Cardiovascular health	Images from 10 cardiovascular disease patients and 10 healthy subjects	Extracted standard biochemical assay, one-minute ECG signal, and infrared thermogram of skin area. Computed RR interval from ECG signals using Pan-Tompkins algorithm and HRV time domain factors. Applied Naïve Bayes classifier.	Accuracy: 90.0; Sensitivity: 80.0; Specificity: 90.0
Mishra et al., 2019 [105]	Tumor detection	20 breast thermograms from 30 patients	Used a robust technique and the scale-invariant feature transform to extract features from breast thermograms. Applied feature reduction using PCA and conventional classifiers.	KNN (with Scale invariant Feature Transform): Accuracy: 98.0

TABLE 4. *(Continued.)* Summary of studies that applied infrared thermography in healthcare applications using ML approaches.

Selvathi and Suganya 2019 [103]	Diabetic eye diseases	283 thermal eye images of diabetic patients and healthy subjects	Extraction of textural and statistical features, support vector machine classifier, five-fold cross validation	Accuracy: 86.2; Sensitivity: 94.1; Specificity: 79.2
Mishra and Rath 2019 [104]	Tumor detection	Breast thermogram images from 37 patients and 19 healthy subjects	Extracted images from temperature matrix and texture features from images. Applied traditional classifiers.	RF classifier: Accuracy: 97.0
Nagori et al., 2019 [25]	Cardiovascular health	539 images (253 continuous intra-arterial blood pressure)	Measured intra-arterial blood pressure. Segmented regions of interest based on histogram of oriented gradient features. Applied AUC-ROC curve and RF classifier.	Accuracy: 73.0; Sensitivity: 65.0; Specificity: 62.0
Gogoi et al., 2019 [106]	Tumor detection	12 malignant, 23 benign, 25 healthy images	Conducted intensity-based, temperature-based, and tumor location matching analyses. Extracted temperature and thermal features from thermograms. Applied SVM classifier with radial basis function kernel.	Accuracy: 83.2; Sensitivity: 85.5; Specificity: 73.2
Cho et al., 2019 [26]	Mental health	93 sets of data from 17 participants	Combined thermography and photoplethysmography to identify stress. measured blood volume pulse and temperature changes in the tip of the nose caused by dilation. Low-level characteristics that represent cardiovascular variability were extracted.	Accuracy: 78.3
Bandalakunta et al., 2019 [107]	Metabolic conditions	246 images (150 diabetics without complications, 36 with complications, 60 healthy)	Extracted regions of interest from diabetic foot images. Computed mean temperature, maximum temperature, mean temperature difference, and relationship between corresponding regions of each foot. Performed statistical analysis and applied Mobile net model.	Accuracy: 91.0
Magalhaes et al., 2019 [108]	Skin health and dermatology	320 skin neoplastic lesion images	Applied image analysis techniques with machine learning to identify skin tumor types. Used SVM classifier.	Accuracy: 84.0; Sensitivity: 91.0
Magalhaes et al., 2019 [2]	Skin health and dermatology	46 images (16 malignant, 30 benign skin lesions)	Analyzed static and dynamic thermal images of skin lesions. Extracted thermal properties from skin lesion images and applied conventional machine learning classifiers.	SVM classifier: Accuracy: 84.2; Sensitivity: 91.3; Specificity: 11.0
Saednia et al., 2019 [109]	Tumor detection	Breast images from 90 patients	Extracted thermal-based features and texture parameters (gray-level co-occurrence matrix, gray-level run length matrix, neighborhood matrix). Applied leave-one patient out cross validation and RF classifier.	Accuracy: 87.0
Sathish et al., 2019 [110]	Tumor detection	100 breast cancer images (47 abnormal, 53 normal)	Extracted local energy features from wavelet sub-bands. Applied feature selection based on random subset feature selection and genetic algorithm. Used SVM (Gaussian) classifier.	Accuracy: 91.0; Sensitivity: 87.2; Specificity: 94.3
Vardasca et al., 2019 [102]	Metabolic conditions	39 active diabetic foot ulcer images	Measured mean temperature of regions of interest from diabetic foot images. Determined thermal asymmetry value for each region of interest. Applied conventional machine learning classifiers.	KNN classifier: Accuracy: 81.2: Sensitivity: 80.0; Specificity: 100.0
Madhavi et al., 2019 [111]	Tumor detection	Breast images from 32 normal subjects and 31 abnormal patients	Analyzed breast thermogram images. Extracted texture features and applied kernel principal component analysis for selection of significant features. Used SVM classifier.	Accuracy: 96.0; Sensitivity: 100.0; Specificity: 92.0
Benjumea et al., 2019 [112]	Skin health and dermatology	7 melanoma lesions and 1 basal cell carcinoma thermographic images	Extracted regions of interest from skin lesion images. Applied segmentation using k-means clustering and performed histogram analysis.	Thermography images containing melanoma have a higher average value in the red area compared to other areas

TABLE 4. *(Continued.)* Summary of studies that applied infrared thermography in healthcare applications using ML approaches.

Bauer et al., 2020 [34]	Other health conditions	Cellulite thermographic images from 212 female volunteers	Applied 9 feature extraction methods to cellulite thermographic images. Used 9 conventional classifiers and different combinations of extraction methods and classifiers.	Histogram of oriented gradients method with artificial neural network classifier: Average accuracy: 80.9
Kudrin et al., 2020 [113]	Skin health and dermatology	165 benign, 185 benign acquired melanocytic, 10 malignant neoplasm images	Evaluated clinical parameters for skin neoplasm. Applied principal component analysis and KNN classifier.	High sensitivity and specificity values of more than 90%
Aydemir et al., 2020 [114]	Acute appendicitis	112 patients, 112 healthy subjects	Histogram, Shapiro-Wilk test, Levene test, Mann-Whitney U test, t-test, Pearson analysis	Proposed technique of thermal assessment of abdominal pain is promising for appendicitis diagnosis.
Thirunavukkarasu et al., 2020 [115]	Type II diabetes	80 facial thermograms from type II diabetes patients and 80 facial thermograms from 80 healthy subjects	Extraction of Haralick textural features, gray-level co-occurrence matrix, temperature features, support vector machine	Accuracy: 89.4
Ilo et al., 2020 [116]	Cardiovascular health	164 peripheral artery disease patients and 93 healthy subjects	Computation of ankle-brachial index, measurement of differences in feet skin temperature	Proposed technique is effective in identifying temperature differences between feet, it is not effective in diagnosing artery disease.
Rashmi et al., 2021 [40]	Metabolic conditions	600 thermal images from 100 healthy and obese participants (50 boys, 50 girls)	Extracted 15 statistical textural features from thermograms of study regions for obesity. Applied scale invariant feature transformation, PCA, and conventional machine learning classifiers.	SVM classifier: Accuracy: 98.0
Brzezezinski et al., 2021 [117]	COVID-19 pneumonia	101 thermal images of upper backs (over lungs)	Extraction of texture and shape features from images, receiver operating characteristic curve	Area under curve: 85.0 Sensitivity: 92.0
Nag et al., 2021 [118]	Metabolic conditions	334 plantar thermograms from 122 diabetic patients and 45 non-diabetic subjects	Segmented foot planar thermograms using lazy snapping. Extracted statistical, textural and wavelets-based features from regions of interest. Applied Fisher's Discrimination Ratio for feature selection and conventional machine learning classifiers.	DT classifier (combination of all features): Accuracy: 97.8
Resmini et al., 2021 [119]	Tumor detection	1400 dynamic infrared thermography, 80 static infrared thermography images	Segmented breast thermograms and extracted texture features. Applied conventional machine learning classifiers.	SVM classifier: Accuracy: 95.0
Karthiga and Narasimhan 2021 [120]	Tumor detection	60 benign and malignant breast thermograms	Extraction of statistical, geometrical and textural features, curvelet transform, support vector machine classifier	Accuracy: 93.3
De Credico et al., 2022 [121]	Cardiovascular health	32 healthy subjects (20 women, 12 men)	Used facial infrared thermography to estimate heart rate variability parameters. Computed and evaluated heart rate variability metrics using photoplethysmography signals. Applied support vector regression-based model with linear kernel.	Proposed method produced associations between approximated and measured heart rate variability metrics.
Qu et al., 2022 [122]	Respiratory health	Prostate cancer-related medical data (1,933,535 items of identifiable and structured medical data from 8000 patients)	Extracted location and shape features from thermal images of back for pneumonia detection. Applied principal component analysis and conventional machine learning classifiers.	SVM classifier (binary classification): Accuracy: 93.0

TABLE 4. *(Continued.)* Summary of studies that applied infrared thermography in healthcare applications using ML approaches.

Dey and Rajan 2022 [123]	Tumor detection	7 healthy, 18 abnormal breast thermograms	Extracted red plane from thermal images. Applied Otsu's thresholding and seeded region growing techniques. Computed bilateral ratios of statistical features.	Accuracy: 92.0; Sensitivity: 94.1; Specificity: 87.5
Cardone et al., 2023 [124]	Tumor detection	Thermal videos of 13 patients with heterogenous brain tumors	Extracted time and frequency domain features. Applied conventional machine learning classifiers with 10-fold cross validation.	SVM (with radial basis function kernel): Accuracy: 90.5; Sensitivity: 84.6; Specificity: 93.7
Rim et al., 2023 [125]	Musculoskeletal health	Data from 1000 patients with radiculopathy and herniated lumbar discs at the L3/4, L4/5, and L5/S1 levels, as well as data from healthy individuals	Used clinical variables for the classification of lumbosacral radiculopathy images. Applied conventional machine learning classifiers and analyzed body temperature image data based on machine learning. Utilized Brier score for evaluation.	RF classifier: Balanced accuracy: 66.0
Clara et al., 2024 [126]	Tumor detection	Breast tissue samples	Utilized IR and thermal sensors with machine learning algorithms and Arduino system for breast cancer analysis.	The proposed method enables accurate analysis of breast tumor.
Tan and Lim 2023 [127]	Wrist joint inflammation	70 wrist joints of 70 rheumatoid arthritis	To determine if IR may be helpful in detecting joint inflammation at the wrist categorised according to its clinical manifestations.	For all imaging parameters, statistically significant differences (all $p<0.05$) were detected (a) between the 4 wrist groups

SVM: SUPPORT VECTOR MACHINE; KNN: K-NEAREST NEIGHBOR; AUC-ROC: AREA UNDER THE RECEIVER OPERATING CHARACTERISTIC CURVE; DT: DECISION TREE; PCA: PRINCIPAL COMPONENT ANALYSIS; RF: RANDOM FOREST.

TABLE 5. Summary of studies that applied infrared thermography in healthcare applications using DL approaches.

Author, year	Application	Participant/data information	Features and methods	Findings/Results (%)
Mambou et al., 2018 [128]	Tumor detection	Breast images from 24 patients, 43 healthy subjects	Pre-processed images and extracted features from pre-trained Inception V3 deep model. Classified images using support vector machine classifier.	Proposed method proves that using computer aided diagnostic tool is important for infrared-image processing.
De Freitas and Lucas Grassano 2018 [129]	Tumor detection	Static dataset: 177 healthy breast images, 42 breast cancer images. Dynamic dataset: 1900 healthy images, 840 non-healthy images	Extracted quantitative data from breast images. Applied CNN and seven accuracy measures.	Static dataset: Accuracy: 98.0
Thirunavukkarasu et al., 2019 [44]	Metabolic conditions	Tongue thermogram images obtained from 140 subjects	Diabetes is classified based on thermal fluctuations on tongue. Segmented hot spot regions based on colour histogram. Extracted gray level co-occurrence matrix features and applied conventional machine learning classifiers.	CNN: Accuracy: 94.2
Tello-Mijares et al., 2019 [130]	Tumor detection	35 healthy subjects and 28 abnormal breast images	Combined curvature function k with gradient vector flow. Applied CNN and conventional machine learning classifiers. Extracted texture descriptors and used 2-fold cross validation.	CNN: Accuracy: 100.0
Cruz-Vega et al., 2019 [53]	Metabolic conditions	110 foot thermogram images of diabetic mellitus patients	Used fuzzy logic histogram-based technique for image segmentation. Applied artificial neural networks, SVM classifier, and Diabetic Foot Thermograms Network deep model.	KNN classifier: Accuracy: 85.3
Ekici and Jawzal, 2019 [50]	Tumor detection	Thermal breast images from 140 participants	Features are extracted from breast images using image statistics, image analysis, and biodata. Applied CNN and Bayes optimization.	Accuracy: 98.9

TABLE 5. *(Continued.)* Summary of studies that applied infrared thermography in healthcare applications using DL approaches.

Abdel-Nasser et al., 2019 [131]	Tumor detection	DMR-IR thermogram dataset	Extracted features using six texture analysis techniques. Calculated malignancy score and performed statistical analysis. Applied multilayer perceptron deep neural network.	Histogram of oriented gradients features: Accuracy: 98.9
Kakileti et al., 2019 [132]	Tumor detection	Breast thermal images from 180 patients	Utilized 4 types of convolutional neural networks. Evaluated using accuracy, dice coefficient, and Jaccard index. Compared with patch-based classifiers.	For the three performance metrics, encoder-decoder models outperformed patch-based classifiers.
Kakileti et al., 2019 [133]	Tumor detection	900 breast thermal images	Implemented cascaded CNN and multi-view heuristics-based segmentation.	Dice index: 0.92
Iqbal et al., 2019 [134]	Tumor detection	Breast thermogram images from 38 patients 40 healthy subjects	Developed a digital back-end processor with an application-specific focus on thermography. Pre-processed thorax thermal images and extracted texture features. Applied dual classifier (SVM, CNN).	Sensitivity: 90.1; Specificity: 91.8
Farooq and Corcoran 2020 [135]	Tumor detection	Breast images from 287 patients	Pre-processed acquired images and extracted features using pretrained Inception-v3 deep neural network. Applied Contrast Limited Adaptive Histogram Equalization.	Accuracy: 80.0
Yousefu et al., 2020 [136]	Tumor detection	Breast images from 208 participants	Extracted deep thermomic features from ResNet-50 pre-trained model. Applied PCA and deep autoencoder for dimensionality reduction. Used random forest classifier for classification.	Accuracy: 78.2
Mishra et al., 2020 [137]	Tumor detection	680 breast images for training (Visual Lab group of Federal Fluminense University)	Applied CNN with pre-processing, segmentation, and classification steps.	Accuracy: 95.8
Alsaedi et al., 2021 [138]	Tumor detection	150 healthy, 150 breast cancer images	Developed hybrid modality for the detection of breast cancer using microwaves and infrared thermography. Applied thermography technique to identify heat pattern and used CNN.	Detection of tumor location: Accuracy: 99.0
Macedo et al., 2021 [139]	Tumor detection	Breast thermogram images from Brazilian dataset	Extracted shape and texture features using Zernike and Haralick moments. Applied feature selection using swarm intelligence. Implemented CNN, extreme learning machines, and SVM.	Proposed method decreases computational time and enhances diagnostic accuracy
Zuluaga- Gomez et al., 2021 [140]	Tumor detection	DMIR-IR database	Applied CNN and benchmarked various models (Xception, InceptionResNetV2, Inception, VGG16, SeResNet, and ResNet).	Accuracy: 92.0
Torres-Galvan et al., 2021 [141]	Tumor detection	Dataset 1: 219 breast thermograms Dataset 2: 101 breast thermograms	Implemented deep CNN (transfer-learned ResNet-101 model). Augmented training data with geometric transformations. Evaluated using performance metrics and AUC-ROC.	Sensitivity: 92.3; Specificity: 53.8
Sanchaz-Cauce et al., 2021 [52]	Tumor detection	170 healthy, 41 breast cancer images	Pre-processed thermal images (3 views) and grouped personal and clinical data into three categories. Applied CNN and evaluated using performance metrics and AUC-ROC.	Accuracy: 97.0
Ucuzal et al., 2021 [142]	Tumor detection	3504 healthy, 2457 breast cancer images	Pre-processed images and used pre-trained deep models. Developed web-based software for analysis.	ResNet50V2 model: Accuracy: 99.6
Al Husaini et al., 2021 [42]	Tumor detection	DMR database (3 healthy, 3 breast cancer images) Shiraz Cancer Hospital (5 breast cancer images)	Developed smart application with cloud computing. Trained deep CNN model inception (192 layers). Applied thermal image parameters and compression techniques.	Accuracy: 100.0

TABLE 5. *(Continued.)* Summary of studies that applied infrared thermography in healthcare applications using DL approaches.

Gade et al., 2021 [143]	Tumor detection	760 healthy, 760 abnormal breast thermogram images	Implemented interpretable deep learning model with multiscale analysis domain (seven parallel deep neural networks). Applied empirical wavelet transforms in two dimensions with fixed boundary points. Utilized hold-out validation and five-fold cross validation methods.	Accuracy: 99.5
Madura et al., 2021 [49]	Eye localization for ocular surface disease	2003 infrared eye thermal images	Intersection over union, average precision, mean average precision parameters, You Only Look Once V2 deep network.	Mean average precision: 97
Jingxin et al., 2022 [46]	Respiratory health	CT images of 50 patients with pulmonary lesions and 30 healthy subjects	Performed object detection and semantic segmentation of lung images for COVID-19 classification. Applied ResNet 50 deep model.	Mean accuracy: 98.4
Da Silva et al., 2022 [48]	Fever(temperature analysis of eyes, forehead, ears)	781 thermographic images of the face from 111 participants	You Only Look Once (deep learning) Network	Mean average precision: 97.0
Dey et al., 2022 [145]	Tumor detection	300 healthy and 580 breast cancer training samples	Applied Roberts and Prewitt edge detectors. Extracted features using pre-trained DenseNet 121 model and performed Grad-CAM analysis.	Accuracy: 98.8
Chatterjee et al., 2022 [144]	Tumor detection	DMIR-IR breast images dataset	Used CNN (VGG16) for feature extraction from breast thermographic images. Applied dragonfly algorithm for selection of optimal features and Grunwald-Letnikov technique.	Proposed method achieved 100% accuracy as compared to using VGG16 model directly for classification.
Mammoottil et al., 2022 [146]	Tumor detection	322 breast mammograms from 161 patients, thermal breast images from 293 patients	Pre-processed and segmented images. Combined images with personal and clinical data. Applied CNN for analysis.	Accuracy: 93.8; Sensitivity: 88.9; Specificity: 96.7
Alshehri and Alsaeed 2022 [147]	Tumor detection	1542 breast thermal images (762 carcinogenic, 780 non-carcinogenic) from 56 patients	Pre-processed grayscale images and extracted features using CNN. Applied bidirectional long short-term memory, attention mechanism, fully connected, sigmoid, and classification layers. Used 10-fold cross validation technique.	Accuracy: 99.5
Goncalves et al., 2022 [148]	Tumor detection	864 healthy, 193 breast cancer images	Pre-processed images by converting 2D images to 3-channel images. Applied three CNN models (DenseNet-201, ResNet-50, VGG-16). Used genetic algorithm and particle swarm optimization techniques.	DenseNet-201 model: Accuracy: 91.7
Ensafi et al., 2022 [149]	Tumor detection	Static thermogram images from database for mastology research (frontal-45, lateral-45, lateral45 data)	Analyzed multiple views of breast thermal images. Applied transfer-based deep learning models and extracted hand-crafted features.	Proposed method resulted in an increase in sensitivity (2-15%) and specificity (2-30%) compared to other deep models or hand-crafted methods.
Mahoro and Akhloufi 2022 [150]	Tumor detection	Database for Mastology Research	Used TransUNET transformer for segmentation of breast images. Applied four CNN models with pre-processing, data augmentation, segmentation, and classification. Performed K-fold cross validation (3,5,10).	ResNet-50 deep model: Accuracy: 97.3; Sensitivity: 97.3; Specificity: 100.0, 96.9, 99.7 (healthy, sick, unknown classes)

TABLE 5. *(Continued.)* Summary of studies that applied infrared thermography in healthcare applications using DL approaches.

Chebbah et al., 2022 [151]	Tumor detection	170 breast images from open-source database	Applied U-net model for segmentation. Conducted vascular network analysis and textural assessment on segmented thermograms. Segmented images were used to extract features, and SVM was used for classification.	Accuracy: 94.4
Der Strasse et al., 2022 [45]	Musculoskeletal health	Infrared images of 45 patients with clinical suspension of bone fracture	Investigated bone trauma via infrared images of ankle, foot, clavicle, forearm, hand, and leg. Analyzed mean temperature of images and compared regions of interest of same size and location.	Proposed method could underscore crucial physiological data linked to vascularization of bone fracture.
Mohamed et al., 2022 [51]	Tumor detection	DMR-IR database	U-Net model, CNN deep model	Accuracy: 99.3; Sensitivity: 100.0; Specificity: 98.7
Luo et al., 2023 [43]	Cardiovascular health	Leg thermogram images from 373 patients	Used thermal images and hypoperfusion parameters for hypoperfusion severity classification in critically ill patients. Applied six deep learning models and evaluated using AUC-ROC.	ResNet model: Accuracy: 94.0
Pramanik et al., 2023 [152]	Tumor detection	Database for Mastology Research	Implemented a deep learning model (SqueezeNet) using transfer learning. Applied Genetic Algorithm and Grey Wolf Optimizer for reduction vector dimension.	Accuracy: 100.0
Martinez and Gonzales et al., 2023 [153]	Tumor detection	52 healthy and 64 breast cancer thermographic images	Compared deep learning and traditional machine learning methods using K-fold cross validation. Applied seven machine learning algorithms with feature selection. The authors implemented deep learning model with sigmoid activation function and assessed predictive uncertainty.	Accuracy (deep model): 87.0 Compared to traditional ML, DL model has lowest predictive uncertainty for the screening of patients with and without breast cancer
Tsietso et al., 2023 [154]	Tumor detection	DMR database	AlexNet, extraction of region of interest from thermograms, multiple views of images, neural network	Accuracy: 90.5; Sensitivity: 93.3
She et al., 2024 [47]	Skin health and dermatology	Database of 1008 skin images	Applied transfer learning on DenseNet model for skin images. Used Monte-Carlo cross validation and combined visual and thermal information.	Recognition rate: 96.4
Fasihi-Shirehjini and Babapour-Mofrad [155] 2024	Metabolic conditions	Dataset comprising plantar thermal images of diabetic and non-diabetic feet	Analyzed plantar thermal images of diabetic and non-diabetic feet. Extracted features using ImageNet pretrained ConvNeXts. Applied PCA and classified images using fully connected layers, SVM, and LR.	Proposed method yielded the best results with logistic regression classifier: Accuracy: 100.0
Khomsi et al., 2024 [156]	Tumor detection	1400 various cases of breast images	Implemented feed-forward deep neural network model and created 3D breast model. Evaluated using coefficient of determination and mean square error metrics.	Mean square error: 19.4 Coefficient of determination: 99.8
Bohlouli et al 2024 [157]	Tumor detection	83 breast cancer images and 132 healthy breast images	Generative Adversarial Network,ResNet-152 transfer learning model,	Accuracy: 90.0

CNN: CONVOLUTIONAL NEURAL NETWORK; KNN: K-NEAREST NEIGHBOR CLASSIFIER; SVM: SUPPORT VECTOR MACHINE; LR: LOGISTIC REGRESSION; PCA: PRINCIPAL COMPONENT ANALYSIS; AUC-ROC: AREA UNDER THE RECEIVING OPERATING CURVE.

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