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A PERSPECTIVE STUDY ON SCALABLE COMPUTATION MODEL FOR SKIN CANCER DETECTION: ADVANCEMENTS AND CHALLENGES

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Abstract. In the realm of scalable computing, the quest for early detection of skin cancer takes on a new dimension, demanding robust and efficient algorithms capable of handling vast amounts of data. This article delves into the burgeoning field of intelligent computing, where scalable solutions are imperative for processing the multitude of skin lesion images generated daily. Leveraging cutting-edge deep learning and machine learning techniques, researchers strive to develop automated systems capable of swiftly analyzing lesion features like symmetry, color, size, and shape.Through a comprehensive literature review, this paper explores the strides made in skin lesion detection, focusing on scalable computing approaches that accommodate the growing volume of medical imaging data. By identifying significant contributions in classification and segmentation methods, the article not only sheds light on the latest advancements but also offers guidance for aspiring researchers navigating the complexities of skin lesion analysis. Ultimately, the fusion of scalable computing and intelligent algorithms holds promise in revolutionizing early detection efforts, potentially saving countless lives by swiftly identifying and treating skin cancer at its onset.

Key words: Machine learning, deep learning, skin cancer and scalable computing

1. Introduction. One of the most important health problems that the world faces is cancer [1]. As a consequence of the sickness, the human body may exhibit a wide range of distinct symptoms and locations. One of the most common and significant forms of cancer that affects women is breast cancer. Within the male population, prostate cancer is one of the most well-known and fatal forms of cancer. Mesothelioma is a kind of skin cancer that affects both men and women and often results in death. This particular kind of skin cancer is the most common type in the United States, and nine percent of the population is affected by it. In addition, according to the findings of a recent study, the most common cause of death in the United States that is attributed to cancer is melanoma, which causes skin cancer. According to the findings of a recent study, the number of newly diagnosed instances of cancer and deaths attributed to cancer has been assessed.

In the United States of America, skin cancer is one of the most prevalent forms of cancer. Due to the fact that the skin is the largest organ in the body, skin cancer is the kind of cancer that occur most often in people [2]. Two of the most prevalent kinds of skin cancer are melanoma and non-melanoma skin cancer. Melanoma is quite rare. The skin cancer known as melanoma is a rare and potentially lethal form of the disease. Despite the fact that melanoma skin cancer accounts for just one percent of all cases, the American Cancer Society claims that it has a greater prevalence of fatalities [4]. In the cells known as melanocytes, melanoma is able to progress. When healthy melanocytes grow out of control, they transform into cancerous tumors. All areas of the body are susceptible to being affected by it. It is common for individuals to have it on their hands and face since they are constantly exposed to the sun. The only method to cure melanoma cancer is to detect it at an early stage, before it extends to other parts of the body and causes the individual to suffer a horrible death [5]. Melanomas may take many distinct forms, including nodular melanoma, spreading melanomas, and lentigo

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malignant [3] skin tumors. Melanomas are common in the United States. Squamous cell carcinoma (SCC) and basal cell carcinoma (BCC) are the two kinds of non-melanoma skin cancer that comprise the majority of cases (SGC). BCC and SCC are the most frequent types of skin cancer. When it comes to the epidermis, these three forms of cancer are present in the intermediate and upper layers. A low likelihood of the disease spreading to other parts of the body is associated with this kind of cancer. Melanoma malignancies are much more difficult to treat than non-melanoma tumors, which are far simpler to cure.

An extraordinary increase in the use of artificial intelligence (AI) has been seen over the course of the last decade. These variables have led to a considerable progression in computer technology as well as the construction of new algorithms, as well as a spike in the amount of digital data that has been created. At the moment, artificial intelligence (AI) is at the center of a broad variety of tasks that are performed on a daily basis, and it is becoming an increasingly crucial component of the conveniences that are commonly available today. Because these technologies are starting to have an effect on the economy and industries throughout the world, artificial intelligence has become an essential component of important activities in the fields of engineering, finance, and other fields. When it comes to the classification of skin cancer using computer vision, which is a subset of artificial intelligence, deep learning has allowed artificial intelligence to approach near to the level of a dermatologist based on research studies that have been conducted over the last two years. When it comes to dermatology, on the other hand, the usage of these models has been the subject of experimentation for generations. The purpose of this research is to determine the role that dermatologists play in the creation of these models, with the end goal of describing the growth of artificial intelligence in the diagnosis and assessment of skin cancer.

The most essential aspect in determining a patient's prognosis is the early identification of skin cancer, which is a commonly known fact. When it comes to the identification of skin cancer, specialists often use the biopsy method. For the purpose of diagnosis, samples of skin lesions that are thought to be cancerous are taken and submitted to a pathologist. This is a cumbersome, uncomfortable, and time-consuming operation. In the future, the use of computers may make the process of diagnosing skin cancer far easier and more expedient. A variety of non-invasive therapies are available for the purpose of diagnosing skin cancer. These treatments may be used regardless of whether or not the symptoms are suggestive of melanoma. Steps in the process of detecting skin cancer include collecting a picture, processing it, dividing it into smaller pieces, identifying the characteristic that is pertinent, and lastly determining if the image is benign or malignant.

The field of machine learning has been significantly influenced by deep learning in recent times. For the purpose of learning, the area of artificial neural network algorithms is regarded to be at the forefront of the discipline. Their structure is modeled after the way the human brain processes information. The fields of bioinformatics, pattern identification, and voice recognition are all examples of sectors that have discovered applications for deep learning. The use of deep learning systems has been shown to be more successful than the use of traditional machine learning methodologies in some fields. Over the course of the last several years, a variety of deep learning algorithms have been researched for their potential use in the field of computerized skin cancer diagnosis. The objective of this research is to create methods that make use of deep learning in order to identify skin cancer at an earlier developmental stage.

Artificial neural networks (ANN), convolutional neural networks (CNN), self-organizing neural networks (KNN), and generalized adversarial networks (GANs) are some of the technologies that may be used for the detection of skin cancer. The purpose of this study is to conduct a comprehensive and methodical literature review of the many approaches that may be used to diagnose skin cancer. There has been a significant amount of research conducted on this topic. In light of this, it is of the utmost importance to collect and evaluate the research, classify them, and synthesise the findings of the studies that are already accessible. For the purpose of conducting a comprehensive systematic review of skin cancer detection systems that are based on deep neural network-based classification, we used search strings to retrieve relevant content of interest. Our investigation was concentrated on conferences and publications of a high standard. Following the application of our multi-stage selection criteria and assessment technique, we devised a search strategy that resulted in the discovery of sixty-five articles that were of interest. The works in question were subjected to a comprehensive analysis and evaluation from a wide range of viewpoints. Although there have been some encouraging developments in the detection of skin cancer, there is still space for improvement in the diagnostic procedures that are now in use.

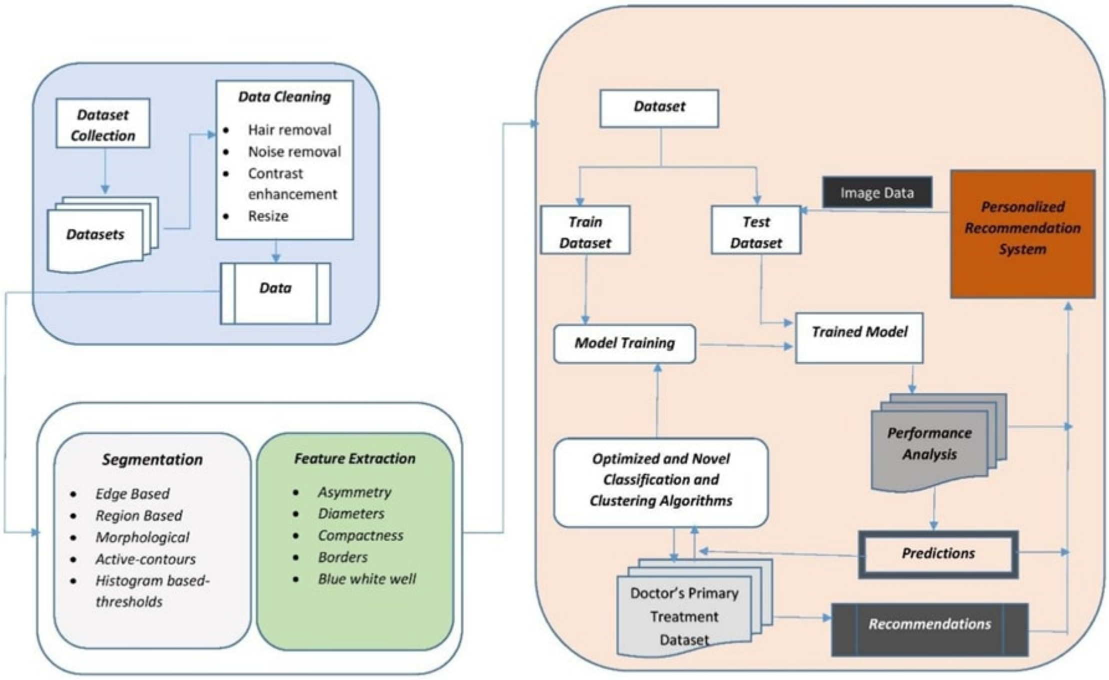

Fig. 1.1: Generic architecture for Early Diagnosis of Skin Cancer Using Machine Learning

1.1. Role of diabetes in Skin Cancer. Individuals who have diabetes mellitus have an increased risk of developing a certain kind of cancer. On a number of times, researchers in Taiwan have focused their attention on individuals who have diabetes mellitus and the risk of developing skin cancer [6]. Using information obtained from the Taiwan Longitudinal Health Insurance Research Database, this retrospective cohort research evaluated the likelihood of acquiring melanoma and non-melanoma skin cancers (NMSCs) between persons who had diabetes and those who did not have diabetes. Patients with diabetes mellitus, who also have an increased tendency for cell proliferation, have raised insulin and IGF (insulin-like growth factor) levels, which results in the production of mitogen and anti-neoplastic effects, as well as malignant cell transformation.

Melanoma is the most common type of skin cancer, followed by squamous cell carcinoma, basal cell carcinoma, malignant tumor of sebaceous glands and sweat glands, and non-melanoma skin cancer (NMSC). Melanoma is the most common form of skin cancer. The incidence of these two malignancies was among the highest ever recorded in Taiwan [7]. In spite of this, the risk of skin cancer in diabetics has gotten a lower amount of money for scholarly investigation. In light of the fact that only a limited number of studies have shown a connection between diabetes and malignant melanoma, it is not obvious whether or not this link is indeed present in other nations.

1.2. Personalized Diagnosis and Early Treatment Recommendation System for Melanoma Patients. There is a possibility that machine learning algorithms may bring about a significant change in the existing way of detecting skin cancer. In order to enhance cancer diagnosis rates, they may concentrate their limited resources on those individuals who are most likely to be affected by the illness. If they were used, patient visits would be simplified, and there would be an increase in the number of referrals to dermatologists. Another possible use for dermatologists is the utilization of mobile apps for the purpose of providing clinical decision help throughout the course of service.It is possible that visual explanations of the qualities that a model uses for classification might also be valuable in diagnosis; with the use of a decision support app, a physician could get a comprehension of both the prediction made by the model and the classification method that it uses. Dermatologists may utilize this information to either narrow down the probable reasons of a patient's symptoms or incorporate it in a full-body skin exam for a more precise diagnosis [8]. This is only one of the many possible applications for this information.

Almost two-thirds of all mobile apps that are relevant to dermatology provide users the ability to monitor their own skin lesions by making use of the camera that is built into their device. with the purpose of providing patients with the ability to engage in teleconsultation with their physicians on any concerns they may have. Users are able to detect lesions, follow diagnostic algorithms, register customized prescription regimens, and record symptoms via the variety of possibilities offered by individualized monitoring programs. These applications also allow users to document symptoms. Users are able to take digital photographs of moles and other lesions via the use of an application called LoveMySkin Mole Map, which was developed by the University of Michigan Medical Center. Additional programs that allow users to capture photographs of moles include FotoSkin, Embarrassing Bodies – My MoleChecker, and UMSkin-Check. You may download these applications from the internet. A three-dimensional model is used by Apre Skin in order to classify and record moles, hence elevating the degree of documentation [9].

Two recent instances of the rapid spread of telemedicine into mobile technology platforms for the delivery of health care are direct-to-patient and patient-directed teledermatology as well as teledermoscopy. This is most likely owing to the introduction of smartphone dermatoscopes that may be used in combination with high-resolution built-in digital cameras and high-speed Internet connectivity. Teledermatology may be able to provide a solution to the problem of patients who are unable to attend dermatologists owing to factors such as transportation, financial restrictions, or time limits. In the present day, around eight to ten percent of direct-to-consumer teledermatology practices are exclusively mobile-based teledermatology services. The teledermatology app known as DermCheck costs a monthly fee of twenty dollars for unrestricted access to the dermatological concierge service. In contrast, other teledermatology services charge anywhere from forty to one hundred dollars for a single appointment. The screening of patients for skin cancer is one of the most prominent applications for these services; however, they may also be used to treat a wide variety of other dermatological conditions as well [10].

Patients have the ability to initiate a consultation with a dermatologist by using a smartphone application that adheres to the principle of direct patient care. Generally speaking, they use a method known as "store-and-forward," in which patients submit their medical histories and digital photographs for the purpose of being evaluated by dermatologists. These dermatologists then offer a consultation and appropriate treatment within a time limit that has been established beforehand. It is possible that you should make use of teledermatology apps if you are worried about suspicious lesions that are present on your skin. A good example of this would be the Skin Cancer App Dermatologist, which offers a consultation within twenty-four hours and costs a fee of nine dollars. An opinion from a dermatologist is inferred from the name of the app, despite the fact that the app itself just specifies that it is an opinion from a "genuine doctor." When compared to face-to-face consultations, the diagnostic accuracy of teledermatology and teledermoscopy varies, however there are certain situations in which they are comparable to one another. According to a recent study, a significant number of direct-to-consumer teledermatology platforms did not identify or certify the consulting physician or hired physicians who were not licensed to practice medicine in the state of the patient or even in the United States. Additionally, it was rare to comply with guidelines in the area of teledermatology, such as providing patients with a choice of experts and presenting a report back to their primary care physician. In the same study, three out of fourteen consultants failed to appropriately identify a nodular melanomas as being concerning. Quite commonly, there is uncertainty about the quality of the service that is being provided. Concerns have also been raised about the lack of privacy safeguards and regulations that are included in mobile teledermatology apps.

When sensitive photos are involved and the treating physician or provider is located outside of the proximity zone, this particular situation is very concerning. The fact that the majority of smartphones destined for the future generation have the capability to monitor personal information, such as the location of the user, makes this situation much more precarious. There are just a few of programs, such as SkyMD and DermEngine, that provide you the opportunity to protect your privacy. It has been determined that a few of these apps do not meet the criteria established by the American Academy of Dermatology for teledermatology of superior quality.

Table 1.1: Types of Intelligent Mobile applications for skin cancer detection

Type of Mobile Application	Pros	Cons
Applications that educate the users about early diagnosis of skin cancer	Inexpensive and most effective way to educate patients about symptoms of skin cancer that helps the individual for early diagnosis	Many of such applications were not backed up with a systematic process to verify the accuracy of the information preloaded in the application
Mole Mapping: This technique enables the app users (patient) to share their images pertaining to area of concern	This technology enables the patient to collect their own images for self-examination	Quality of the image is variable on not suitable for diagnosis
Teledermatology: This mechanism enables a platform for patient-directed virtual treatment	This kind of applications provide access to dermatologists without temporal and geographic barriers	Many of such applications are not adhered to the standards of telemedicine

A relatively recent occurrence in the field of teledermatology is known as patient-directed teledermoscopy. Patients have the ability to take dermatoscopic images of their skin using the MoleScope, a smartphone-mounted dermatoscopy device that costs $99, and then transmit these photographs to a dermatologist for diagnosis. This procedure is not commonly utilized, requires specialized tools, and is most likely best suited for high-risk patients whose dermatologists are knowledgeable with this modality. Despite the fact that research has proved that this method is theoretically practical and acceptable to patients, it is not generally employed.

New ethical concerns need to be addressed if this new technology is to be fully realized while minimizing the amount of harm that is caused to patients. This is because smartphone apps are becoming more widespread. Before the usage of mobile apps can be regarded ethically acceptable, there are a number of issues that need to be addressed, including concerns about the privacy of patients, informed consent, transparency of data ownership, and protection of data privacy. The rapid advancement of this technology has resulted in the construction of a system that is capable of certifying a level of care being beyond its capabilities. Although guidelines for teledermatology have been created, the degree to which these standards are adhered to is still largely up to the discretion of the practitioner.

This paper aims to undertake a comprehensive literature review focusing on technology-enabled options for early diagnosis of skin cancer. Recent research have shown a predominant emphasis on developing advanced machine learning algorithms to detect skin cancer in its early stages. It was noted that only a small number of studies focused on creating a customized recommendation system for early detection and treatment of skin cancer. This study involves a thorough examination of several research articles from different publications to determine the extent and development of research. The article is structured as follows: part 2 explains the research methods used in the study, while section 3 provides an in-depth overview of studies that have significantly contributed to predicting skin cancer in its early stages. Section 4 provides information on the research gaps and potential areas for additional study in skin cancer diagnosis. Section 5 provides the last comments of the study.

2. Research Methodology. The primary goal of this SLR is to provide the groundwork for future studies by outlining the areas of study that need more investigation into the topic of intelligent algorithms for the early detection of skin cancer, as well as any gaps in the current body of knowledge. It has been noted that there is a lack of well-interpreted SLRs addressing the important algorithms involved in creating deep learning algorithms for effective picture analysis, even though there have been numerous published SLRs tackling different obstacles to the development of efficient protocols in technology-enabled cancer treatment. The first step is to establish a review protocol, as shown in figure 2.1. This will allow us to formulate initial Research Questions (RQs) based on a systematic search of over-indexed journal databases using keywords related to the wireless sensor network domain. Our goal is to find recent studies that have addressed this topic and have focused on developing efficient algorithms for computation in sensor networks. Step two of the review methodology involves identifying relevant preliminary studies; step three involves documenting and interpreting the results of the thorough study; and finally, step four involves determining the scope of future research by using the established inclusion and

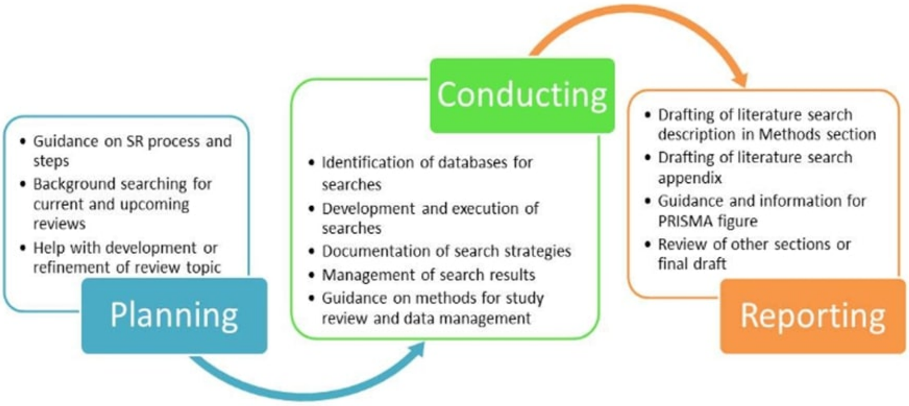

Fig. 2.1: Systematic review process [11]

Table 2.1: Combination of search strings to identify relevant articles from scientific databases

Skin Cancer OR skin Lesion OR Melanoma OR Non Melanoma Skin Cancer
AND
Epidermis OR Hypodermis OR Dermis OR Cancerous tumor
AND
Basal Cell Carcinoma OR Squamous Cell Carcinoma,OR Merkel Cell Cancer
AND
Dermatologist OR Surgical Oncologist OR Hierarchical Based OR radiation oncologist
AND
Computational Intelligence algorithms OR heuristic algorithms OR machine learning techniques OR Meta heuristic algorithms
AND
Personalized Medicine OR Telemedicine OR Mobile Applications OR Biopsy OR MRI OR CT-SCAN
AND
Systematic Study OR SLR OR Mapping Study OR Review

exclusion criteria.

2.1. Search strategy. The search strategy is developed by applying a predetermined set of keywords to indexed databases such as IEEE, ACM, SPINGER, SCIENCE DIRECT, etc. Table 2.1 shows the combination of search strings used for preliminary article search, which are related to computer networks and wireless sensor networks:

In the initial cases based on above search strings 148 relevant research papers addressing the domain of wireless sensor networks were identified within a range of a decade (2011-2021) directly from scientific databases the dissemination of the articles over various databases is depicted in Table 2.2.

2.2. Defining Research Questions. The need and impetus for doing a systematic review are part of the research question formulation process shown in Table 2.3 which is seen as an essential part of analyzing an SLR. Based on the insights provided by [12], the PICO technique is used to craft robust research questions that will generate high-level evidence to back up the review's findings.

2.3. Preliminary selection. First, 148 articles are culled from scientific databases using the search terms given in table 1.1. Next, we check the articles' titles to see whether they address the topic adequately. Second, we used a Table 2.4 to keep track of which articles made the cut and which ones did not.

Subsequently, 58 research articles meeting the inclusion and exclusion criteria were chosen to document the review. It should be mentioned that these articles provide the necessary information to expand the study's

Table 2.2: Dissemination of identified articles over various scientific databases

S. No	Database	No. Of Papers
1	IEEE	55
2	ACM	25
3	TAILOR and FRANCIS	15
4	SPRINGER	27
5	SCIENCE DIRECT	26
Total		148

Table 2.3: Formulation of Research Questions

Acronym	Definition	Motivation	Research question
P	Problem	Gain knowledge related to in-depth analysis of various deep learning based image processing algorithms	RQ1: What are the various deep learning algorithms utilized for the purpose of segmentation of images in the field of medical diagnosis?
I	Intervention	Understand the state of art algorithms involved in developing efficient prediction and accuracy while detecting skin cancer	RQ2: What are the state of art algorithms and dataset evaluated while diagnosing skin cancer at early stages?
C	Comparison	Comparative analysis of existing algorithms to evaluate the variation of prediction accuracy	RQ3: Generate analysis of various existing algorithms and analyze their performance metrics
O	Outcome	Identify open research issues and challenges in technology enabled intelligent diagnosis of skin cancer	RQ4: What is the future scope of research in deep learning enthused skin cancer detection?

Table 2.4: Inclusion and Exclusion Criteria

Inclusion Criteria	Exclusion Criteria
Articles that Included algorithms centric methods, deep learning architectures and mathematical assertions designed in the context of addressing skin lesion detection	Articles with an ambiguity in the context of the implementation tools and data sets
Articles developed based on the evidential research that is formulated with well defined implementation details and simulation results along with the inclusion of tools and datasets required for the segmentation and prediction metrics relatives to	White papers and lecture nodes regarding published in the context of the architectural perspective of skin cancer
Articles that are primarily implemented in the computer science domain in specific to the areas of machine learning, deep learning and Artificial Intelligence.	Articles that are written in other than the English language.
Articles that are written in the English language.	

scope in relation to skin cancer detection.

3. Review of Various Existing Studies. Melanoma is a very dangerous kind of skin cancer that kills tens of thousands of people every year. If melanoma is to be treated rapidly, the medical community will need to find solutions to a number of novel challenges. Researchers seeking a better treatment for melanoma should sift through literature reviews based on previous studies that were carried out in different eras and places. Conducting a literature assessment of relevant sources is crucial for gaining a better understanding of the research environment. Using objective methods, researchers may begin studying medical image processing and how to cure melanoma using new technology.

In this section, we review the segmentation and classification methods, and we address the problems that came up when reviewing the literature on sample data. Many studies have investigated the possibility of improving medical research by identifying melanoma using deep learning techniques for dermoscopy images.

3.1. Review of Studies on Skin Lesion Segmentation. Various methods for segmenting the lesion region in dermoscopic pictures are described thoroughly in this portion of the paper.

An approach that employs histogram-based clustering estimations and neutrosophic c-means clustering (NCM) for the input dermoscopy photographs was developed by Amira Ashour and colleagues (2018) [13] for successful skin lesion diagnosis. Sort the dermoscopy images' pixels according to neutrosophic criteria first. The HBCE algorithm calculates using h-v and v-h approaches. The public data set from ISIC 2016 is used for the implementation; it contains 379 test photos and 900 training photographs. Effective training and testing based on the availability of ground truth images is necessary since the valuation is done using ISIC 2016 data sets. In comparison to the gold standard NCM method that does not include HBCE, the results of the proposed research are much better.

An automated technique for lesion segmentation using semi-supervised learning is described by Seetharan-iMurugaiyan Jaisakthi et al. (2018) [14]. The method consists of two steps: pre-processing and segmentation. In the pre-processing step, the bi-linear interpolation technique is used to scale the images, and the CLACHE algorithm is used to optimize the images with uneven lighting. After that, the Frangivesselness filter from FMM is used to swap out the pixels that represent hair. In a segmentation procedure, pixels with consistent color and texture characteristics are used to identify lesion zones. Using this method's boundary and region information, which is reinforced by using RGB-based kmeans clustering, we can divide the foreground image into approximately defined "lesion areas."

A fresh approach to addressing this problem was suggested by Sahar Sabbaghi et al. [15] in 2018. With its expertise in color assessment, the Quad-Tree system can tell if a melanoma is benign or malignant only by looking at its color. Examining melanomas in this study included using geometric distances and concentratic quartiles. A higher level of contrast between the lesion and background areas is achieved before processing begins. Lesions without color contrast may be treated using morphological treatments like top-hat and bottom-hat surgeries. The hybrid thresholding method divides the segmentation process into two steps, allowing for accurate identification of lesion borders. In order to find core lesions, we adjust the Otsu threshold. Then, we use an adaptive histogram algorithm to make them longer. Based on the characteristics of the ROC curve, it is determined that the SVM classifier performs the best.

Brammya et al. (2018) [16] created a novel meta-heuristic method by using the DHOA-NN approach. The buck's eyesight is five times stronger than a human's, which makes tracking him down much more difficult. Above the horizon, it is difficult to see what is happening. There seems to be hunting going on in the vicinity. The goal function is used to iteratively update positions until the best possible location is discovered. It follows that DHOA-convergent NN outperforms competing methods in terms of performance.

Amira Soudani et al. (2019) [17] presents a segmentation recommender that is built on top of community sourcing and transfer learning. In order to get features from pre-trained architectures such as ResNet50 or VGG16, the convolutional parts are used. The CNN serves as a classifier, while the five nodes that make up the output layer stand in for different segmentation techniques. It is possible to identify local traits from a variety of angles using the two-dimensional structure of dermoscopy photographs. The results back up our prediction that our suggested strategy might lead to a segmentation approach for skin lesion detection.

Examining the CNN architecture, Walker et al. (2019)[18] demonstrates the usage of the inception v2 network for dermoscopy image classification as benign or malignant. A technique known as stochastic decent gradient is used for training the inception v2 parameters inside the deep learning framework. Among the many possible impacts that dermoscopy pictures might bring about are visual characteristics and sonification. The research demonstrates that tele-dermoscopy imaging has a very sensitive malignancy detector and enhanced accuracy in both pigmented and non-pigmented lesions.

Teck Yan Tan and colleagues (2018) [19] created the Particle Swarm Optimization (PSO) method, which is used to identify skin cancer using dermoscopy photographs. The method's stages of operation involve tasks such as segmenting skin lesions and extracting features, optimizing features based on PSO, and performing classification. Swarm leaders divide the initial population in half and then guide each half to choose the best possible solution while avoiding the worst. This approach lessens the possibility that a PSO model converges too quickly by using international and domestic food and enemy signals, attraction, and mutation-based exploitation. Subswarm leaders are bolstered using random walks such as Gaussian, Cauchy, and Levy. There is a plethora of searchability provided by probability distribution and dynamic matrix representation. The proposed method has enhanced melanoma classification accuracy and has performed well on benchmark problems with either a uni- or multi-modal structure. If you want further evidence of how great the proposed method is, you may use the Wilcoxon rank sum test.

According to Mohammed, Al-Masni et al. (2018) [20] , a new approach of segmenting dermoscopy pictures based on a fully resolution convolution network may investigate the full resolution characteristics of every pixel in the input image. The cross entropy loss function is employed by CNNs for pixel-wise categorization. There are no prior or post processing steps required in the suggested method for obtaining full resolution images. On the network levels, back propagation is used to reduce training error. FrCN outperforms the most recent deep learning segmentation methods in comparison to two publicly accessible datasets, the ISBI 2017 Challenge and PH2 datasets.

Image segmentation approaches are compared by Anuj Kumar and his colleagues (2018) [21]. Analysis and identification of relevant characteristics or objects within an image is known as segmentation. An essential component of image analysis is edge-based segmentation, which displays discontinuities of the edges in terms of intensity. An image threshold value is calculated and then compared to the pixel value in order to eliminate broken edges using the canny edge detector. That an edge exists is based on the higher pixel value. There must be a boundary around the region chosen for segmentation based on region. First, a pre-processing phase minimises noise while keeping the picture information that allows them to get a well-segmented image. Therefore, it can be concluded that the edge detector canny delivers the best performance when employing region expanding, which speeds up the segmentation process when compared to region splitting and merging.

A novel approach to handling CNN variable tuning for process fine-tuning was proposed by Guotai Wang and colleagues (2018) [22] and is called Bounding box and Image Tuning-based Segmentation (BIFSeg). Intuitive 2D and 3D medical picture segmentation is achieved via a deep learning-based approach. The proposed weighted loss function in this method lends credence to both supervised and unsupervised image-tuning. The information in the bounding box teaches a convolutional neural network (CNN) to generalize hidden objects by learning common structures like saliency, contrast, and hyper-intensity across different objects. As a result, compared to prior interactive segmentation methods, the suggested framework BIFSeg increases accuracy while decreasing the amount of time and effort required from the user.

Due to the fine-grained nature of the primary diagnosis of melanoma that may be achieved by early screening and further dermoscopic investigation, such as biopsy and histological evaluation, automated categorization of lesion pictures is a tough issue. As inputs, pixels and illness labels are taken into account while training a single CNN for skin lesion classification. According to this, the AI can categorise skin cancer with improved accuracy when compared to dermatologists, and so achieves higher performance in the detection of most frequent malignancies and the worst forms of skin cancer.

Qaisar et al. (2011) proposed unsupervised segmentation of multiple lesions and improved region-based active contours [23]. Additionally, a level has been automatically chosen using the iterative thresholding approach. Another factor that has helped keep the curves stable is the application of smoothing constraints to the Courant-Friedreichs-Lewy function. In order to assess their method, 320 dermoscopy images of the skin were examined. Their segmentation results, genuine detection rates, and false positive rates have all been enhanced.

In their 2017 publication, Euijoon Ahn and colleagues described a computer-assisted diagnostic method for automatically identifying melanoma by lesion segmentation [24]. Poor skin lesion segmentation performance is caused by a number of challenges with standard segmentation algorithms. These include unclear lesion borders, low contrast between the lesion and surrounding skin, and the lesion touching the image bounds. Improved lesion categorization from surrounding skin regions is attainable using methods derived from sparse representation models and novel background detection algorithms. According to the proposed Bayesian framework, lesions are better described. We validate our approach by comparing it to various traditional lesion segmentation techniques and unsupervised saliency detection methods, based on a comparison of two public datasets. That being said, our method is superior than the others. Applying a saliency-optimization approach might further enhance lesion segmentation.

An algorithmic strategy called computational approach was developed by Roberta et al. (2016) [25] to detect skin lesion sorts based on assessment of the attributes collected from photographs. Their plan includes using a support vector machine, an anisotropic diffusion filter, and an active contour model devoid of edges. Researchers have used many techniques to segment and categorize skin lesions. In order to segment skin lesions in a skin image, Eliezer and Jacob (2016) [26] presented a feature learning method that finds the most essential parts of the image. An innovative method for learning from dictionaries without human supervision called Unsupervised Information-Theoretic Dictionary It was explained how learning works and how it has been used to the segmentation of skin lesions. Results from this research demonstrate that the proposed approach is generalizable to other image segmentation problems.

Andrea et al. (2016) [27] introduced a fast and completely automated way to segment skin lesions in dermoscopy pictures. A training phase was omitted from the application of the Delaunay Triangulation to the skin lesion mask extraction process. Several research have been conducted using the public photo databases.

The co-segmentation methodology was introduced in a study by Leonardo et al. (2017) [28]. It is a new method for segmenting MR images that combines the segmented Biological Target Volume with the segmented Gross Target Volume. Jessica and Filipe (2017) offered fuzzy values that were used to construct a new segmentation algorithm called the melanoma segmentation algorithm. They put their method to the test using 571 photographs taken from the standard ISDI dataset; among them, 446 showed benign skin lesions and 125 depicted malignant melanoma. Their method fared better than the existing algorithms when measured using metrics including balanced accuracy, sensitivity, and Jaccard index. They found that fuzzy-value segmentation was the most successful method out of the bunch.

Hamidi et al. (2017) [29] created a new method for automatic image segmentation by combining saliency with the Otsu threshold approach. Their system, which took skin type and other factors into account, generated a color saliency map and a skin feature saliency map. In addition, a more accurate skin picture was produced by combining the two saliency maps. In order to get more accurate skin lesion borders using the histogram distribution of the pictures, their segmentation approach used a new optimization function to change the usual Otsu threshold strategy. By implementing their algorithm, they demonstrated its superiority in terms of effectiveness and accuracy. Their novel algorithm outperforms and is more robust than existing methods, according to the results of their testing.

Mohamed et al. (2018) [30] created a new way to segment data using full-resolution convolutional networks. The suggested method does not need any pre- or post-processing steps for things like artefact removal, low contrast adjustment, or further enhancement of segmented skin lesion boundaries. An evaluation of the proposed method was conducted using the PH2 dataset and the IEEE International Symposium on Biomedical Imaging (ISBI) 2017 Challenge, both of which are publically available.

Using these highly discriminative qualities in a new segmentation algorithm and a skin lesion detection search method was proposed by Neda and Babak (2018) [31]. Also, a novel two-component speed function was used to carry out the segmentation method utilizing the contour propagation technique. Based on data collected from the skin lesion's periphery, they further included a fresh set of features. These photographs were used to map the peripheral areas of the skin lesions to log-polar space using an existing Daugman's transformation. A variety of features were then extracted from these pictures. They discovered that both the new features used and the linear Support Vector Machine (SVM) for melanomat classification were successful in differentiating melanoma from normal nevus, as compared to other techniques that utilize the existing RUSBoost classification algorithm. To determine which characteristics are most useful for classification, each classifier employs a sequential feature selection method.

3.2. Review of Studies on Detection of Melanoma using Medical Dermasocpic Images. Local Directional Patterns, Local Binary Patterns, and Convolutional Neural Networks are among the feature extraction strategies proposed by Manjunath Rao et al. (2020) [32] and processed by an SVM classifier for effective learning of melanoma lesion pictures. High levels of skin exposure to ultraviolet (UV) radiation are a major contributor to the development of melanoma. Consider both the melanoma and non-melanoma photos for assessment. The SVM classifier is used to classify the three extraction methods. Consequently, the LBP system's classification using the SVM classifier coupled with the polynomial kernel function is more accurate. Advanced LBP might be developed in the future to identify melanoma at an early stage.

There are three high level characteristics that are crucial for the diagnosis of malignant melanoma, and these features are simplified by adding the human interpretation of data on the suggested features, as discussed in Vikash Yadav et al. (2018) [33]. Detection at an early stage is critical, since melanoma is a deadly form of skin cancer that is exacerbated by sun exposure and pre-malignant moles. Comparing the high-level asymmetric features to the low-level asymmetric ones, the suggested high-level features perform well for concave borders. Skin cancer detection and classification may be improved by developing them as an additional tool.

Melanoma may be detected at an early stage with the use of a computer-aided detection (CAD) system, which lowers death rates. Preprocessing, lesion segmentation, feature extraction, feature selection, and classification are all parts of the method. The DullRazor is used to remove the hair and pre-process the lesion, making it easier to see. A more precise segmentation of the lesion is achieved by combining the innovative uniform distribution approach with the active contour method and using the additive rule of probability. It is possible to identify the form and appearance of the lesion using the local intensity gradients distribution by using HOG features derived from the colour, texture and HOG features. It's hard to argue with the improved accuracy and efficiency of the newly proposed diagnostic procedures. PH2 is a publicly accessible dataset including 200 photos that dramatically outperforms previous algorithms when compared. As a consequence, it can be stated that the use of SVM in conjunction with the Boltzman Entropy technique offers better results on entropy-based characteristics.

Electronic shaving (E-Shaver) is an improved technique for removing hair from dermoscopic pictures than the Dull Razor, according to the work of Kiani and colleagues (2011) [34]. The detection of hair direction in the skin using random transform and subsequent Prewitt filters is critical for an effective hair removal procedure. Dermoscopic pictures may be improved by using average thresholding and smoothing to eliminate noise and non-hair features. So it is regarded to be the quickest and easiest method for hair removal that works.

Multi-level feature extraction may be performed by executing decomposition and segmentation effectively, according to a new technique by Sina Khakabi et al. (2012) [35]. There is no need for pre-processing for colour uniformity or artefact removal with this method. Using spatial and colour data, the development pattern of the lesion may be obtained. Tree-based depiction of lesion development patterns is generated by matching each pixel sub-cluster to an individual node in a tree structure. An extensive feature set is made possible by the model's capacity to extract information from various levels of the tree structure. As a result, it's considered an effective framework for extracting features and training models for accurate lesion segmentation.

By analysing images, Omkar Shridhar Murumdar et al. (2015) [36] provide a non-invasive approach that is crucial for diagnostic purposes. Image analysis may provide insight into the lesion's ambiguous information. Steps 1 and 2 form the basis of the proposed system. The Otsu thresholding segmentation delivers excellent results since it is unsupervised. Second, the feature extraction tool, which is the second phase, may be used to evaluate and study photographs appropriately without requiring any type of invasion into the human body. Dermoscopic pictures are processed using a technology to extract the ABCD rule, which identifies the characteristics as asymmetry, border structure, colour variation, and lesion diameter. The TDV value is computed using the values derived from features. The greater the TDV number, the more likely it is that melanoma is present.

Using the ABCD rule, Sharmin Majumder and her colleagues (2018) [37] have devised a framework for determining whether a lesion is malignant or benign. The existence of hair in skin photographs is regarded to be the most difficult duty, even if the differences between malignant and premalignant photos are aesthetically comparable to a greater degree. The difference between the highest and lowest Feret diameters of the best fit ellipse to the skin lesion is used to extract additional features. In the suggested technique, a Back-propagation Neural Network is employed as the classifier (BNN). In the suggested technique, the weights evaluated are the same for all photos and demonstrated to be accurate for all types of photographs.

3.3. Review of Studies on early diagnosis of Skin Cancer using Machine Learning Techniques. Neural networks play a crucial role in the detection of skin cancer. Their structure is built upon interconnected nodes. Their architecture is quite similar to the human brain in terms of the connections between neurons. In order to address specific problems, their nodes collaborate. Once trained, neural networks can execute a certain task at a very high level. We trained neural networks to classify images and identify various skin cancers as part of our study. Many different types of skin lesions are part of the ISIC collection.

According to Xie et al. [38], skin lesions may be classified as either benign or malignant. The proposed system consisted of three parts. The first step in lesion detection in images was to use a self-generating neural network. In the second portion of the investigation, details such as the tumor's border, texture, and color were collected. In all, the system was able to obtain 57 features, including 7 additional ones associated with the description of lesion borders. Principal component analysis (PCA) was used to minimize the feature dimensionality, which led to the selection of the optimal set of features. The last stage was to classify lesions using a NN ensemble model. Ensemble NN may benefit from the use of fuzzy NN and backpropagation (BP) NN for better classification results. Various classification algorithms, including KNN and Adaboot, were also compared to the results of the proposed system. With an accuracy rate of 91.11%, the proposed model outperformed the other classifiers by 7.5% in terms of sensitivity.

A method for automated skin cancer detection based on artificial neural networks (ANNs) was proposed by Masood et al. [39]. The article examined the performance of three artificial neural network (ANN) learning techniques: Levenberg-Marquardt (LM), robust backpropagation, and scaled conjugate gradient. A sensitivity of 92.6% for benign lesions and a specificity of 95.1% for malignant lesions were achieved by SCG learning with a doubling of the number of epochs used. We created a mole classification system to help find skin cancer early on [40]. While extracting features, the proposed method adhered to the ABCD rule of lesions. In the ABCD model, a mole is defined by its form, borders, color, and diameter. A mole's asymmetry and borders were evaluated using the Mumford-Shah algorithm and the Harris Stephen method. Under the new approach, any mole that wasn't black, brown, or cinnamon was considered melanoma. Moles that may be malignant melanoma usually have diameters more than six millimeters (mm). With a backpropagation feed-forward ANN, we were able to classify moles with an accuracy of 97.51%. One possible approach to skin cancer diagnostics is an ANN-based backpropagation system [41]. A 2D-wavelet transform was used by this system for the purpose of feature extraction. The proposed ANN model was used to classify the images as either benign or cancerous. An further method for diagnosing skin cancer using ANNs was proposed by Choudhari and Biday [42]. To segment the pictures, an entropy thresholding technique was used. The skin lesion data was analyzed via a gray-level co-occurrence matrix (GLCM). Photos of skin cancer were accurately classified as either malignant or benign by using feedforward neural networks; the resulting accuracy rate was 86.66%.

According to Aswin and coworkers [43], genetic algorithms (GAs) and artificial neural networks (ANNs) may be used to identify skin cancer. The Otsu thresholding approach was used to extract the region of interest (ROI) from medical imaging software called Dull-Rozar. The segmented pictures were then processed using the GLCM method to extract their distinctive properties. For the categorization of lesion pictures into malignant and noncancerous classifications, a hybrid ANN and GA classifier was utilised.

Using digital dermoscopy pictures, Fengying et al. (2016) [44] came up with an innovative method for determining whether melanocytic tumours are benign or malignant. A self-generating neural network extracts skin lesions, and picture attributes that describe tumour colour, texture, and boundary are also retrieved and identified using a neural network ensemble classifier to classify skin lesions. Dermoscopy skin lesion images are too small in the critical medical context for bigger skin lesions. New border feature methods for assessing border abnormalities across the full and partial lesions have been presented by authors to address this challenging presentation. In their novel technique, an ensemble-based classification algorithm has been devised that blends the normal back propagation neural networks with the fuzzy rules known as fuzzy neural networks in order to achieve improved classification precision. In order to test the effectiveness of their method, they ran a series of tests on two different dermoscopy datasets, which included photos of xanthous and caucasian races.

An expert system developed by Suleiman & Akio (2018) [45] is able to identify the presence of skin cancer from simple photographic photographs of diseased skin patches. The ABCDEs rule has been used to identify melanoma photos in their system. The GrabCut algorithm was used to accomplish the segmentation of an input melanoma picture into skin lesions, and image processing techniques were used to extract characteristics such as the shape feature, colour feature, and geometry feature. Furthermore, the support vector machine and the Gaussian radial basis kernel were used to classify all of the collected characteristics as either malignant or non-cancerous. Melanoma and benign photos have also been used in the different tests. At the conclusion of the research, only six characteristics were shown to be useful in identifying melanoma. In [46,47] the authors have been used machine learning techniques to classify the images and extracting the features.

Melanoma classification may now be done utilising the structural co-occurrence matrix of the major frequencies collected from normal dermoscopy pictures, according to Pedro and colleagues (2018). They've improved their classifying abilities. Researchers from Hongming et al. (2018) [48] reported a computer-aided approach for identifying melanocytic tumours from skin scans. Four modules are included in the suggested technique, as well. Finally, a multi-class support vector machine containing extracted epidermis and dermis characteristics was used to classify the skin picture into several categories, such as melanoma, nevus, or normal tissue. When 66 skin cancer photos are used, their experimental findings show that their model delivers a classification accuracy of more than 95% when used.

4. Observations from the Literature Study. This study aims to identify the most common methods used to diagnose and treat malignant melanoma, a deadly form of skin cancer that may metastasis (spread to other parts of the body). The dermoscopic imaging device may magnify lesions, but its complex design makes it hard to visually inspect. Possible resolution to the problem awaits the implementation of an automated system for skin lesion segmentation and a clustering approach. The concept that precancerous moles and sun exposure may develop into melanoma, a kind of skin cancer, is well knowledge. In order to effectively detect melanoma, the literature study found that segmentation and classification algorithms, with or without pre-processing stages, may be applied.Various feature extraction approaches may be used to obtain these properties from the segmented area of the lesion. It is possible to diagnose melanoma.In order to diagnose skin cancer, the majority of the applications rely on dermoscopyphotographs.Unlike their predecessors, most modern dermatologists rely on manual pattern recognition to detect lesions, drawing on their prior knowledge and experience. Using the dermatoscope to extract features from the lesion, also known as ABCD, allows for an accurate diagnosis. It is possible to use K-means clustering to group together the foreground picture's RGB color space, which has high Jacquard indexes and dice coefficients. Convolutional Neural Networks (CNNs) with weight sharing perform well in image-based skin cancer detection, but they are computationally expensive to train and experience noticeable slowdowns when presented with a huge volume of input dermoscopy photographs. Training data sets using the Support Vector Machine (SVM) approach takes a long time, which is one of its downsides. Using training data to discover new features in the problematic lesion area increases the likelihood that the deep learning approach will provide high-quality results. The optimization techniques used in these real-time engineering applications are tested by comparing their results to those of other state-of-the-art optimization algorithms.

Fuzzy logic-based clustering, pattern classification, image segmentation, fuzzy classification, fuzzy logic under time constraints, and classification have all been extensively studied by several researchers in the past. Nevertheless, no approach has shown to be more effective in reliably identifying melanoma images. The melanoma skin lesion photographs show an improvement in all image segmentation, grouping, and classification procedures.

There were many different approaches to learning deep learning, such as neural network and hybrid methods of fully convolutional neural networks, transfer learning, and ensemble approaches. Both automated deep learning algorithms and more human-centered approaches have shown promising outcomes in the detection of melanoma. The number of images that can be used for training and testing is restricted since most datasets are rather small. The proposed methods reliably provide surprising results when tested on large datasets, although over fitting might be an issue when used to smaller datasets. For instance, there are just 200 images in the PH2 dataset. One possible solution to the problem of training with a small dataset is to use an adversarial generative network in conjunction with data augmentation and transfer learning. Some researchers utilize private datasets and images found online. Since these studies and their findings are not available in a replicable format, and since images seen online can be biased, it would be difficult to reproduce them.

4.1. Open Research Challenges. The extensive training required is a major drawback of skin cancer detection methods based on neural networks. For this reason, getting the system trained to accurately assess and understand the features of dermoscopy images is a laborious and resource-intensive process. A further complicating factor is the fact that lesion sizes may vary greatly. An international group of researchers from Italy and Austria took countless pictures of skin lesions, both benign and cancerous, throughout the 1990s. Diagnosis accuracy in locating lesions varied between 95% and 96%. Diagnosing smaller lesions, those measuring just 1 or 2 millimeters in diameter, at an early stage was much more challenging and prone to errors.

Regular dermoscopy databases are dominated by images of fair-skinned people from Western Europe, Oceania, and the Americas. In order for a neural network to correctly detect skin cancer in people with dark skin, it has to be taught to take skin color into consideration. But this can only happen if black people's faces are used to train the neural network. In order to train skin cancer detection algorithms to be more accurate, datasets should include a sufficient number of images of lesions on people with light and dark skin tones.

There is a significant disparity in the databases used for skin cancer diagnosis in real life. Unbalanced datasets include wildly different amounts of images for each kind of skin cancer. Because of the small sample size of the more uncommon skin malignancies seen in dermoscopy images, it is challenging to draw broad conclusions about the disease based on these images alone. Neural network (NN) software requires robust hardware resources with strong GPU capabilities to extract particular lesion morphological features from images. Inadequate processing power hinders deep learning-based skin cancer detection training. Melanoma risk factors that have been discovered by researchers include a pale complexion, light-colored eyes, red hair, and many moles on the body. When both hereditary and environmental variables are included, the chances of developing skin cancer increase dramatically. When combined with existing deep learning approaches, these features have the potential to improve performance.

5. Conclusion. Methods for identifying and categorizing skin cancers have been investigated in this comprehensive study. Using any of these techniques will not put you in danger. Picture segmentation and preprocessing are prerequisites for skin cancer diagnosis, which include feature extraction and classification. Classification of lesion images using ANNs, CNNs, KNNs, and RBFNs is the main aspect of this study. You can't have an algorithm without its drawbacks. Selecting an appropriate classification scheme is crucial for optimal outcomes. Since CNNs are more often linked with computer vision, they significantly outperform other methods when it comes to recognizing image data. Many skin cancer detection research focus on determining whether a certain image of a lesion is cancerous. Unfortunately, patients sometimes wonder whether a certain skin cancer symptom appears elsewhere on the body, and unfortunately, current research does not provide an answer to this issue. Classifying the signal image has been the only focus of the investigation so far. One possible solution to this prevalent question might be to use full-body photography in future studies. Speeding up and automating the process of image capture is automated full-body photography.

A relatively new idea in deep learning is self-organization. It is an example of unsupervised learning that uses the dataset's image samples to look for patterns and correlations. Expert systems may improve their feature retrieval with the use of convolutional neural networks that employ auto-organization strategies. Currently, there is an active research and development effort centered on auto-organization. Improving image-processing systems for the future, when pinpoint diagnosis of disease depends on paying great attention to the smallest features in medical imaging, may need a better examination of these aspects now.

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