10.48047/jocaaa.2025.34.12.14

Review of Computerized Skin Cancer Detection Approaches

Zulkifli Muhammad Kalgo,[1], Ahmad Baita Garko[1,2], Muhammad Saidu Aliero[3]

1-Department of Computer Science, Kebbi State University of Science and Technology Aliero, Nigeria
2-Department of Computer Science, Federal University Dutse, Nigeria
3-Department of Computer Science, Kebbi State University of Science and Technology Aliero, Nigeria

Abstract

Skin cancer is among the most lethal forms of the disease. Skin cancer develops as a result of genetic defects or mutations caused by unrepaired deoxyribonucleic acid (DNA) in skin cells. Since skin cancer is more curable in its early stages and tends to spread gradually to other parts of the body, early diagnosis is desirable. Because of the disease's high fatality rate, increasing prevalence, and expensive medical care, early diagnosis of skin cancer indications is essential. Scientists have developed several early skin cancer screening techniques in response to the seriousness of these issues. Skin cancer is distinguished from melanoma by using lesion features such as symmetry, color, size, and shape. This article presents a comprehensive systematic review of deep learning techniques for early diagnosis of skin cancer. We looked at pertinent studies on skin cancer diagnosis that were published in respectable journals. Research findings are presented utilizing tools, graphs, tables, techniques, and frameworks to facilitate understanding. Lastly, the avenues for further study were also emphasized.

Keyword: Skin cancer detection, deep learning skin cancer, computerized skin disease detection

1.0 Introduction

One of the deadliest types of skin cancer, malignant melanoma, is responsible for 75% of all cancer-related fatalities[1]. Skin cancer is a serious health issue. Over the past several decades, melanoma incidences have rapidly increased in Europe, America, and Australia [2]. Both melanoma and non-melanoma are becoming more common; among persons over 50, the yearly incidence of melanoma is increasing by 0.6%, while the anticipated number of new cases of cutaneous melanoma in 2016 was 76,380, or 4.5% of all new cancer cases [3]. According to projections, there will be about 96,480 new instances of melanoma identified in the US alone, 7,230 deaths from the disease, and that number is likely to increase to 150,000 [4]. Early diagnosis, however, clearly depends on patient attentiveness and a physician's precise assessment. There is little information on the test procedures, and the diagnostic variances are wide enough . Inspection is the main foundation of the diagnosis. Conventional imaging simply records what the human eye can see with a digital camera, but dermoscopy, also known as epiluminescence light microscopy (ELM), requires an experienced specialist to obtain the necessary picture. Researchers have created computational algorithms for automated diagnosis that rely on quantitative metrics in an effort to increase diagnosis reliability [5]. These technologies include machine learning, which can assist medical professionals identify the afflicted areas more quickly and objectively by facilitating quantitative judgment in addition to their expertise.

10.48047/jocaaa.2025.34.12.14

Particularly, Deep learning helps to perform predictive analysis that offers a wide range of information to assess a particular problem and make decision in automated way with high accuracy. Deep learning is a form of modern technology developed by researchers such as deep learning convolutional Mobilenet [5]. Mobilenet has been shown to perform better than expert dermatologists at skin cancer detection. Biological processes such as that the nerve cells present in the brain and how they interact with each other encouraged the development of a look-alike artificial neural network technology called the CNN. A CNN is skilled at learning fast from images that it "gets", learns the patterns, colours and continues to teach itself from what it has learned to improve its performance (a process known as machine learning) (Wibowo et al., 2020). Machine learning utilizes different algorithms among which neural networks has become a very popular tool in the software industry [6]. The existence of neural networks can easily be seen in many digital services like the recommended system.

With regard to image-based applications, the recent growth in strength and popularity of deep learning can also be portrayed in applications on skin cancer, which relies on a multi-stage processing of images to extract increasingly more complex features from them [6, 7]. As the features get extracted at higher-levels, they tend to progressively represent more distinctive and integrated characteristics of the image, thus resulting in high performances for image classification [8].

However, the existing standard dermoscopic datasets contain images of light-skinned people, mostly from Europe, Australia, and the United States. For accurate skin cancer detection in dark- skinned people, a neural network must learn to account for skin color [9]. However, doing so is possible only if the neural network observes enough images of dark-skinned people during the process of training. Therefore, datasets having sufficient lesion images of dark-skinned and light-skinned people are necessary for increasing the accuracy of skin cancer detection systems.

2.0 Literature Review

Deep learning is an intuitive process whose complexity of learning increases with the increase in the number of layers. Due to its high performance, it is regarded as a mature application for medical diagnostics. In recent times, deep learning has contributed significantly for skin lesion classification problems [10]. However, limited data set creates tougher environment for the potential groundbreaking research in medical diagnostics with deep learning. One reason is dependency of the deep learning algorithm on training data size as it requires millions of parameters and large amount of labeled data to learn [11]. When limited data is used to train deep learning model, it uses large amount of its resources to train the model, creating over setting issues. The aim of this section is to conduct Systematic Literature Review (SLR) to investigate the common challenge faced by the existing approaches.

2.1 Conducting Literature Review

This section presents detailed process and procedure for conducting this study review. These processes and procedures are derived from guidelines in [12]

2.1.1 Taxonomy of Literature Reviews

10.48047/jocaaa.2025.34.12.14

This review utilizes a three-tier hierarchical selection to select primary literature that meets the review requirement. The process starts from broader selection requirements and narrows to specific selection requirements, as summarised in Figure 2.

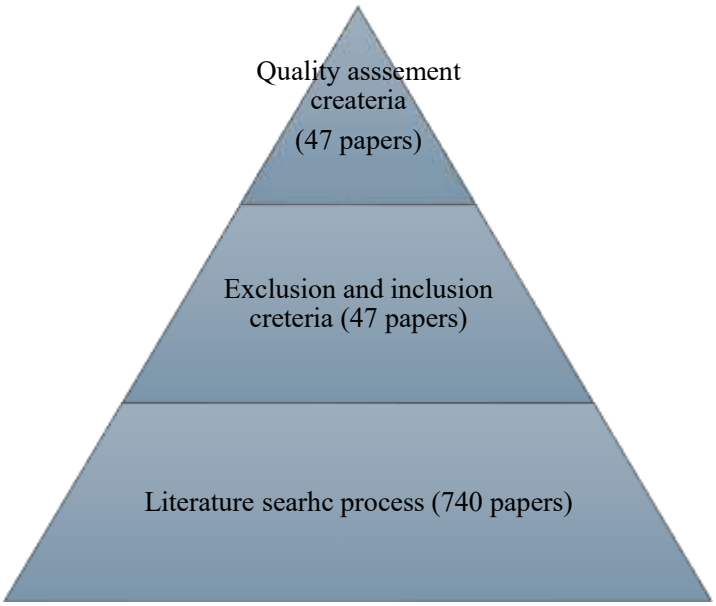

Figure 2: Taxonomy for literature selection

2.1.2 Literature search process

The search process considers published journal and conference papers, books, reports, and online repositories focusing on skin cancer detection. The search process uses four main keywords (“Skin Cancer,” ” Skin Diseases”, “Cancer Disease”, “Melanoma Skin Cancer”and “, Skin Treatment”). Each of the main keywords consists of sub-keywords selected using guidelines suggested by[13]and experienced derived [14-16]. Each main keyword started broadly to gradually narrow down to more specific terms to cover as many skins’ cancer detection with deep learning areas as possible (see Figure 3).

The literature search was performed across five different databases "Scopus", "Elsevier", "IEEE Explore”, "Science Direct", and, "Google Scholar" from the year 2010-2023.

10.48047/jocaaa.2025.34.12.14

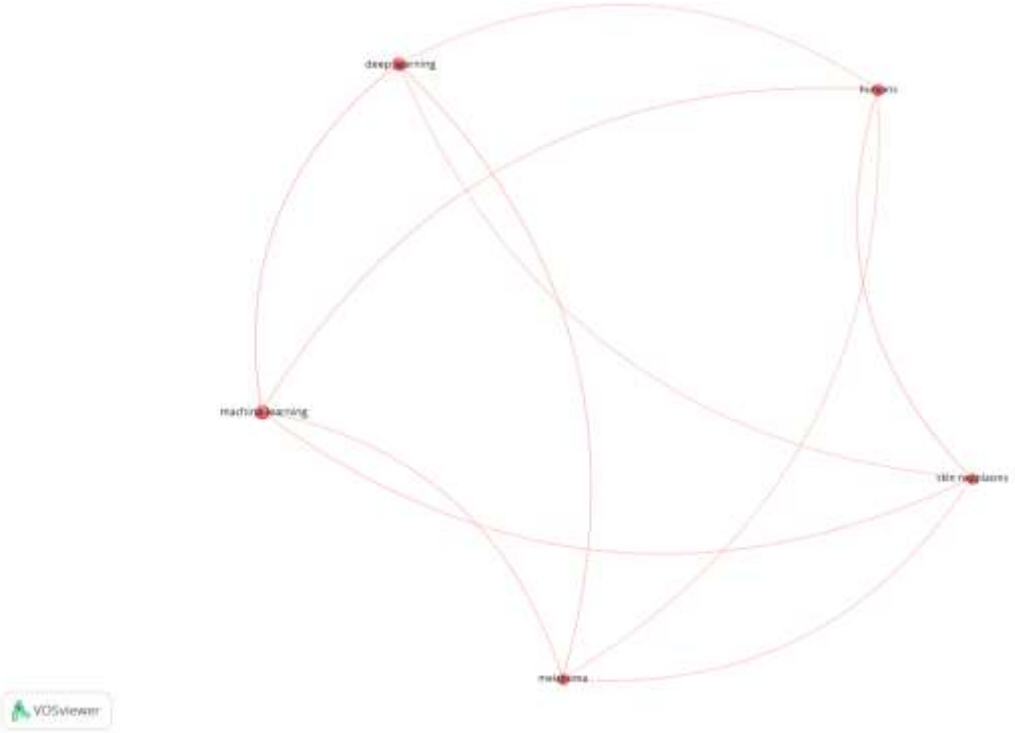

Figure 3: search keyword for skin cancer and sub-keywords

The search output for "Skin Cancer " and sub-keywords resulted in 412 research outputs. The Figure 3 demonstrate the correlation of keywords and their relevance in our search terms.

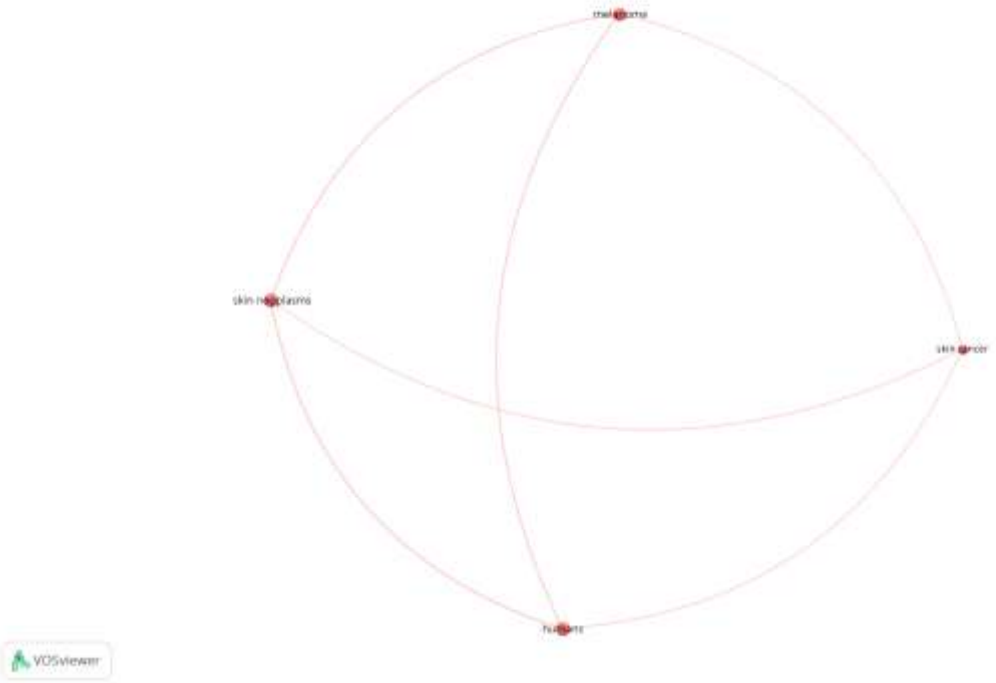

Figure 4: search keyword for skin cancer and sub-keywords

10.48047/jocaaa.2025.34.12.14

Similarly, as can be seen in the Figure 4, search results for "Skin diseases" and sub-keywords results in 317 research output with higher number of similar keywords in extracted research outputs.

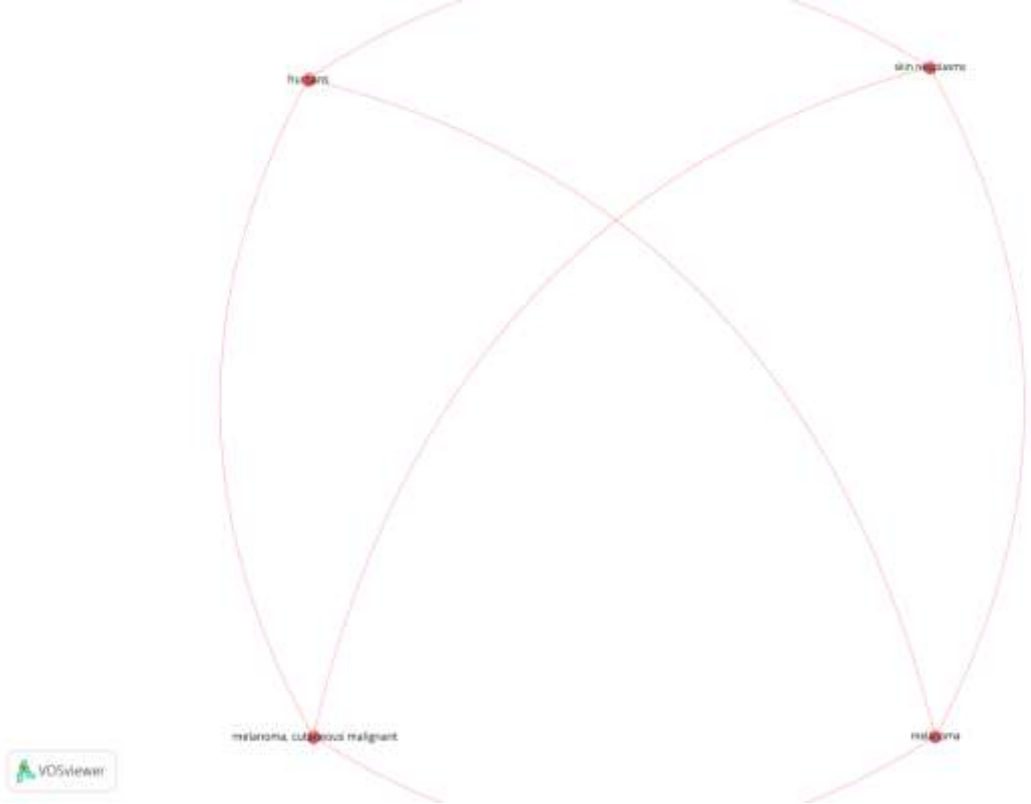

Figure 5: search keyword for DL skin cancer and sub-keywords

Furthermore, the search result of keyword " DL Skin Cancer" with sub-keywords results to 289 research output with number of keywords that has correlation among the extracted research outputs see (Figure 5). Finally, the search result of main keyword "ML skin cancer "and sub-keywords resulted in 189 research outputs. The result in the Figure indicate there is correlation among the keyword of extracted results output for initial investigation in this study.

The entire search process resulted in a total number of 1,207 research outputs. The study moved forward by sorting and removal duplicate literature. This yields the final research outputs to 740 eliminating 467 duplicate studies.

10.48047/jocaaa.2025.34.12.14

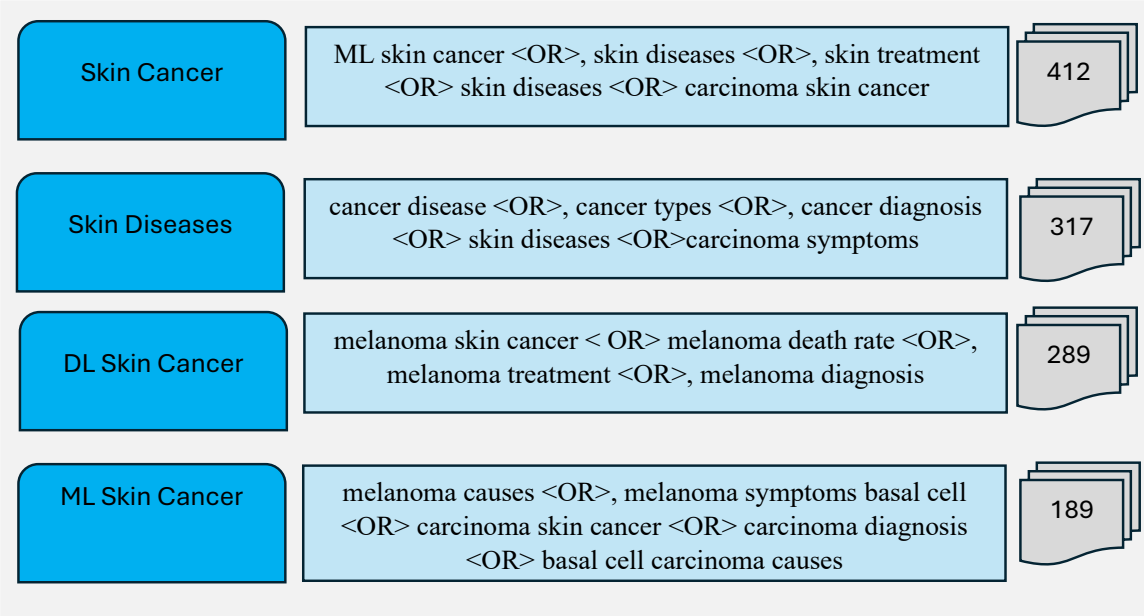

Figure 6: Used search keywords

2.13 Inclusion and exclusion criteria

This review work focuses on the research undertaken around the skin cancer detection in terms of technologies covering skin diseases and other related skin cancer. The research on studies on skin cancer or skin diseases detection and diagnosis is beyond the scope of this work. Work by [13]has been used as a guideline for the review process in general. The inclusion and exclusion criteria are based on published studies' suggestions and experience [13-15, 17]. The goal is to ensure that the identified literature meets the review requirements before an in-depth analysis is carried out.

The study examined the total number of 740 research outputs after applying inclusion and exclusion criteria as presented in Table 1. The final research output was reduced to 47 studies as shown in Appendix A.

Table1. Inclusion and Exclusion Criteria

	Criteria	**Rationale**
	Published peer-review articles related to skin cancer detection	A research article ensures a certain level of quality through a peer-review process with vital information.
	Published peer- viewed articles related to models, frameworks, review methods, or experiences on skin cancer detection	specific skin diseases related to solutions, metrics, and analysis on skin cancer

10.48047/jocaaa.2025.34.12.14

	Published Industrial or organizational reports related to skin cancer detection	Scientific literature or reports on trends of skin cancer detection
	Published peer-reviewed articles related to the conceptual framework or market analysis on skin cancer detection	To be informed of new trends and published skin cancer detection
	One peer-reviewed article not related to skin cancer detection	A research article that is not related to research work was conducted but used as guidelines throughout the study.
	A published peer-reviewed article on skin cancer detection	The objective is to focus on a study that is linked or related to skin cancer detection
	A published peer-reviewed article related to skin cancer detection	To eliminate study focuses on strategy and solutions to maintain the non-computation skin cancer detection
	Literature related to skin cancer that did not meet the criteria of journals indexing	To eliminate studies those are not indexed in Scopus or Scientific Journal Rankings.
	Non-English manuscripts	Non-English littérature on skin cancer détection

2.1.3 Quality assessment criteria

The selected primary research outputs are rated usinga quality assessment evaluation (QAE) technique, and the Database of Abstracts of Reviews of Effects (DARE) procedures defined by [13, 17]. The QAE in this study uses four (4) quality assessment questions (QA1-QA4), and DARE uses three rating factors (0, 0.5, and 1) to evaluate the level of literature contribution based on the set requirements.

QA1: Is the criteria for inclusion and exclusion in the review process well described and appropriate?

The goal is to determine if the inclusion and exclusion criteria is clearly defined and discussed, or is partially implicit and is not defined and hence cannot be readily inferred in the literature.

QA2: Has domain search possibly covered all related work during the literature search?

The goal is to determine whether four (4) or more digital libraries have been searched and some search strategies are added, or all journals addressing the area considered are identified and referenced by authors.

QA3: Has the quality and validity of the included study have been assessed by the reviewers?

The goal is to determine whether the quality criteria considered are clearly defined and separated from the results.

10.48047/jocaaa.2025.34.12.14

QA4: Is the information/literature of concern described adequately? The goal is to determine the detailed information presented in the literature.

NOTE:

Y (yes) indicates inclusion and exclusion criteria are clearly defined in QA1; four or more digital libraries have been searched in QA2; the considered quality criteria considered is clearly defined and separated from results in QA3; and detailed information about the study is presented in QA4.

P (partly) indicates partially defined in QA1; three (3) or four (4) digital libraries have been searched in QA2; part of quality criteria is missing or mixed up with results in QA3; and summary information about the study is presented in QA4.

N (no) indicates criteria not defined and cannot be readily inferred in QA1; a maximum of two (2) digital libraries explored with restricted journal access in QA2; quality criteria are completely missing in QA3; and no result or discussion is presented in QA4.

The following rating factor is assigned, Y= 1, P = 0.5 N=0

The objective of quality assessment analysis is to identify the level of literature quality (introduction, literature review, material and method, and result discussion) and contribution to the research domain of SBEMS. The assessment results of 140 articles are summarized in Table 2, consisting of 139 related and one non-related research article.

The assessment results in Appendix A, show that 23 literature scored a 4/4 rating, 17 literature score 3.5 out of 4. Likewise, 2 score 3 out of 4 and 5 literature score value 2. 1literature is not relevant, scored 0 out of 4. Works of literature with scored count 4 are literature related to deep learning and skin cancer detection that proposed novel solution and experimental analysis and evaluation with metric or critically and analytically presented a compressive review of the proposed solution. While those with a 3.5 score lack intensive experimental analysis or proper evaluation method, the majority of kinds of literature with a score of 4 and 3.5 are published journal articles. Likewise, those with 2 score count present only proof of concept without further experimental analysis that does not fully employ the deep learning and skin cancer detection. The majority of these kinds of literature are conferences. In summary, the information in Appendix A reveals that the maximum number of related literatures considered has satisfied quality assessment questions.

3.0 Literature Review Analysis

This section analyses the literature taking into account factors like trend of publications, their classifications based on the domain of skin cancer detection, classifications based on the approach.

10.48047/jocaaa.2025.34.12.14

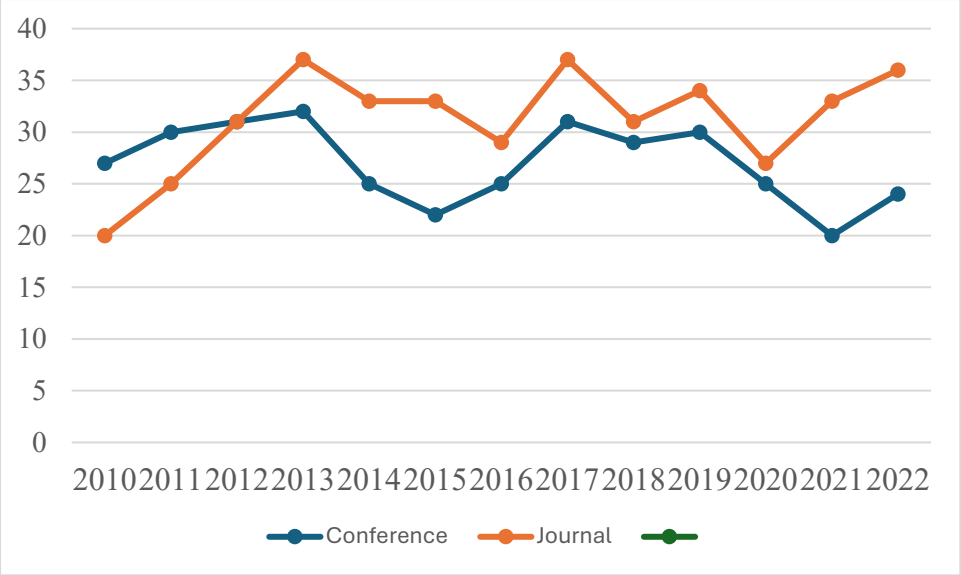

Figure 7: Distribution of literature in the literature across the year

This review paper searched the literature over the last decade. Research on the subject of skin cancer detection appears to be gaining momentum as indicated by the upward trend shown in Figure 7. It is also found that the concerned publications are dominated by journal articles as compared to the conference papers as shown in Figure 7. Publications in general are indication of research and development activities in the field in terms of new technologies and applications. Majority of the conference papers are observed to offer conceptual frameworks around individual technology or application of skin cancer detection. The upward trends in literature indicate that skin cancer detection are becoming increasingly popular across the globe.

3.1 Literature classification

Literature is also classified based on the research domain of skin cancer. A similar classification was conducted in [14, 15, 18] with a goal to investigate which domain of research topic received more attention in industry and academia. The result of this classification is summarised in Table 2.

Table 2: Literature classification

The topic domain	Definition	References	Paper count
Architectures	Refers to high-level shape focused on defining views, perspective, roles together with their arrangement and way they should interact to achieved high skin cancer prediction	S5,S14,S15,S23,S27,	5

10.48047/jocaaa.2025.34.12.14

Platforms/ Models/	Refers to hardware/software infrastructure providing APIs to support real time improvement and execution of package for skin cancer prediction	S3,S4,S6,S24,S26,S31,S 23,S11,S32,S34,S37,S40, S38,S39,S41,43,S45,S46, S2,	21
Framework	Refers to software infrastructure providing reusable additives or perspective to poster improvement of a package for skin cancer prediction	S30,S33,S36,S13,S42, S20,S21,S22,S25, S28,S44	12
Algorithms	Refers to the logical approach consist of steps to arrive at a feasible solution to achieve high skin cancer prediction accuracy	S8,S9,S10,S12,S18,S19, S28,S38,S29,S30,S42, S47,S29,S25,S26,	15
Survey	Refers to the study that provides analytical review on platforms or models, frameworks, and algorithms.	S1, S17,S5,S6, S7	5
		Total	47

The analysis indicates that 21 articles proposed solutions for skin cancer detection, while 5 articles presented review analysis to test, validate, and analyze the existing solutions. The analysis further shows that researchers are putting more effort into developing and integrating algorithms and platforms or models to optimize approach for skin cancer detection. On the other hand, survey, and architectures study received lesser attention in the research domain of skin cancer detection.

3.1 Related work

Skin cancer detection is significantly aided by deep neural networks. They are made up of a collection of connected nodes. Their interconnected neural structure is comparable to that of the human brain. Their nodes collaborate to find solutions to specific issues [19]. After being taught for certain tasks, neural networks become authorities in the fields in which they were trained. Earlier research in this area used deep learning and machine learning to identify skin conditions. Using hierarchical structures, [20] studied the use of deep learning for skin cancer diagnosis. They found that skin lesions had a hierarchical organization that dermatologists take

10.48047/jocaaa.2025.34.12.14

into account when diagnosing them. Automatic methods, however, do not utilize this data, executing the diagnostic in a one-vs.-all manner, where all forms of lesions are taken into consideration.

[21] has present a new approach for the task of hair removal on dermoscopic images based on deep learning techniques. The proposed model relies on an encoder-decoder architecture, with convolutional neural networks, for the detection and posterior restoration of hair's pixels from the images. [22] uses a Dermoscopic photos from the ISIC archive to construct a dataset with two classes, which was then used to categorize benign and malignant cancer kinds. The goal is to raise the categorization score because of early diagnosis. To achieve this, dermoscopic images obtained from a dataset are subjected to several image preparation processes, such as color clarity, edge detection, and noise extraction. Following this processing operation, these processed photos are classified using the InceptionV2 deep learning network. This study's findings show that pre-processing boosts accuracy ratio by 3.33 points, yielding an accuracy rate of 88.66%. while [23] uses a variety of deep convolutional neural network models that have already been trained, including resnet18, squeezenet, google net, vgg16, and vgg19, and applies them to two separate datasets. MODE-NODE and ISIC skin lesion datasets are the datasets. According to testing accuracy measurement, the study concludes that vgg19 is the most suitable DCNN and reached 98.8%.

The research conducted by [24] suggested employing CNN for the detection of skin cancer, In their study, they take into account this technique for raising melanoma detection precision. However, there aren't any sizable datasets of optical lesion images that can be used to train deep networks for dermatoscopic modality. In order to get over these constraints, they propose a transfer learning model to train a collection of deep learning networks and a novel CNN architecture. The convolutional neural network, which produces a detection rate of 97%, achieves the best detection rates. However, improvement was required in the area of detection accuracy, in another research conducted by [25] suggested a lesion indexing network (LIN) based on DL. By extracting more features, they used DL-based LIN to achieve good results. To further improve results, segmentation performance had to be improved.

The author of [26] employed CNN to identify pigmented melanocytic lesions as skin cancer from dermoscopic pictures. Screening for non-melanocytic and non-pigmented skin cancer was challenging, nevertheless. Additionally, its detection accuracy decreased. In other research by [27] proposed a DCNN that includes three phases that work incredibly well to identify skin lesions. To improve contrast, color transformation is initially applied; lesions Lesion boundaries are then extracted using the CNN technique, and deep features are extracted using transfer learning. However, the strategy produced good results in some instances of dataset, but outcomes may vary in other instances. In [28], the author developed a CNN-based model to identify melanoma skin cancer. To enhancing the image prior to and following segmentation, respectively, pretreatment and postprocessing of the image were utilized. By fusing local and global contextual data, the model generated lesion regions. It achieved a decent classification and prediction performance. The results may be more valuable if the execution time were disclosed, which is not the case.

3.2 Potential Research challenges

1. Model training: The substantial training needed for neural network-based skin cancer detection methods is one of the main obstacles. In other words, the system needs to go

10.48047/jocaaa.2025.34.12.14

through extensive training, which takes a lot of time and requires incredibly strong hardware, in order to properly evaluate and interpret the characteristics from dermoscopic pictures.

2. Lesion Sizes: The difference in lesion sizes presents another difficulty. In the 1990s, a team of researchers from Italy and Austria gathered a large number of pictures of benign and malignant melanoma lesions [73]. Up to 95% to 96% of the lesions may be identified with diagnostic accuracy [75]. With smaller lesions measuring just 1 or 2 mm at an earlier stage, the diagnostic procedure was considerably more challenging and prone to mistakes.
3. dataset of light skin people: Images of light-skinned individuals, primarily from Europe, Australia, and the US, are included in the typical dermoscopic datasets that are now available. A neural network must be trained to take skin color into consideration in order to identify skin cancer in dark-skinned individuals [76]. This is only feasible, though, if the neural network sees enough pictures of people with darker complexion to be able to do so. Therefore, to improve the accuracy of skin cancer detection systems, datasets including enough lesion photos of persons with dark and light skin are required.
4. mall Interclass Variation in Skin Cancer Images: There is extremely little interclass variance in medical photos compared to other image types. For example, there is far less variation between photographs of melanoma and nonmelanoma skin cancer lesions than, say, between images of cats and dogs. Additionally, distinguishing a melanoma from a birthmark is quite challenging. Certain diseases have so similar lesions that it is quite difficult to tell them apart. The challenge of picture analysis and categorization is extremely complicated due to this restricted variety [32].
5. Unbalanced Datasets on Skin Cancer There is a significant imbalance in the real-world datasets used to diagnose skin cancer. Each form of skin cancer has a significantly variable quantity of photos in unbalanced datasets. It is challenging to make generalizations from the visual characteristics of the dermoscopic pictures since, for instance, they only have a small number of photos for unusual kinds of skin cancer, whereas hundreds of images for common types [12].
6. Insufficient Access to Strong Hardware Better skin cancer diagnosis depends on the NN software's ability to extract the distinctive elements of a lesion's picture, which requires powerful hardware resources with high graphics processing unit (GPU) capability. One of the biggest obstacles to deep learning-based skin cancer detection training is the unavailability of powerful computational capacity.
7. Application of Diverse Optimization Methods Automated skin cancer diagnosis relies heavily on preprocessing and lesion edge identification. To improve the efficiency of automated skin cancer diagnosis systems, a variety of optimization methods can be investigated, including artificial bee colony algorithm [78], ant colony optimization [79], social spider optimization [80], and particle swarm optimization [81].
8. Examination of Environmental and Genetic Factors Numerous genetic risk factors for melanoma have been discovered by researchers, including red hair, pale skin, light-colored eyes, a lot of moles on the body, and a family history of skin cancer. The likelihood of getting skin cancer increases significantly when these hereditary risk factors are coupled with environmental hazards such prolonged exposure to UV radiation [82]. Better performance can be achieved by combining these elements with current deep learning techniques.

10.48047/jocaaa.2025.34.12.14

4.0 Conclusion

One of the most deadly types of cancer is skin cancer. Unrepaired deoxyribonucleic acid (DNA) in skin cells results in genetic flaws or mutations on the skin, which is how skin cancer is created. It is preferable to diagnose skin cancer early since it is more treatable in its early stages and tends to spread gradually to other regions of the body. Early detection of skin cancer signs is necessary due to the disease's high death rate, rising incidence, and costly medical care. Given the gravity of these problems, scientists have created a number of early skin cancer screening methods. Symmetry, color, size, form, and other lesion characteristics are utilized to identify skin cancer and differentiate it from melanoma. A thorough systematic evaluation of deep learning methods for skin cancer early detection is presented in this work. Relevant research articles on the diagnosis of skin cancer that were published in reputable publications were examined. For easier comprehension, research findings are shown using tools, graphs, tables, methodologies, and frameworks. Finally, the future research avenue were also highlighted.

Author/year	ID	Type	QA1	QA2	QA3	QA4	TOTAL
[29]	S1	Journal	0	0	0	0	0
[3]	S2	Journal	Y	Y	Y	Y	4
[5]	S3	Conferenc	Y	Y	P	P	3
[7]	S4	Journal	Y	Y	Y	Y	3.5
[8]	S5	Journal	Y	Y	Y	Y	4
[30]	S7	Journal	Y	Y	Y	Y	4
[11]	S6	Journal	Y	Y	Y	Y	4
[31]	S7	Journal	Y	Y	Y	P	3.5
[32]	S8	Journal	Y	Y	Y	Y	4
[24]	S9	Journal	Y	Y	Y	Y	4
[25]	S10	Journal	Y	Y	Y	Y	4
[26]	S11	Journal	Y	Y	Y	P	3.5
[19]	S12	Journal	Y	Y	Y	P	3.5
[9]	S13	Journal	Y	Y	Y	P	4
[10]	S14	Journal	Y	Y	Y	Y	4
[12]	S15	Journal	Y	Y	Y	Y	4
[13]	S16	Journal	Y	Y	Y	Y	4
[14]	S17	Journal	Y	Y	Y	Y	4
[15]	S18	Journal	Y	Y	Y	Y	4
[16]	S19	Journal	Y	Y	Y	Y	4
[17]	S20	Journal	Y	Y	Y	Y	4
[18]	S21	Journal	Y	Y	Y	Y	4
[1]	S22	Journal	Y	Y	Y	P	4
[4]	S23	Journal	Y	Y	Y	Y	4
[33]	S24	Conferenc	Y	Y	Y	P	3.5
[34]	S25	Journal	Y	Y	P	P	3
[6]	S26	Journal	Y	Y	Y	Y	4
[35]	S27	Journal	Y	Y	Y	Y	4
[36]	S28	Journal	Y	Y	Y	P	3.5
[37]	S29	Conferenc	Y	Y	Y	Y	3.5
[28]	S30	Journal	Y	Y	P	P	3
[23]	S31	Journal	Y	Y	Y	Y	4
[38]	S32	Journal	Y	Y	Y	Y	4
[20]	S33	Journal	Y	Y	Y	P	3.5
[21]	S34	Journal	Y	Y	Y	Y	4
[22]	S35	Journal	Y	Y	Y	P	3.5
[39]	S36	Journal	Y	Y	Y	P	3.5
[27]	S37	Journal	Y	Y	P	P	3
[2]	S38	Journal	Y	Y	Y	Y	4

10.48047/jocaaa.2025.34.12.14

[40]	S39	Journal	Y	Y	P	P	3
[41]	S40	Journal	Y	Y	Y	Y	4
[42]	S41	Journal	Y	Y	Y	Y	4
[43]	S42	Journal	Y	Y	Y	P	3.5
[44]	S43	Conferenc	P	P	P	P	2
[45]	S44	Journal	P	P	Y	Y	3
[46]	S45	Journal	Y	Y	Y	Y	4
[47]	S46	Conferenc	Y	Y	Y	Y	4

Appendix A

References

1. Ali, M. and T. Aittokallio, *Machine learning and feature selection for drug response prediction in precision oncology applications*. Biophys Rev, 2019. **11**(1): p. 31-39.
2. Ang, J.C., et al., *Supervised, Unsupervised, and Semi-Supervised Feature Selection: A Review on Gene Selection*. IEEE/ACM Trans Comput Biol Bioinform, 2016. **13**(5): p. 971-989.
3. Marcos-Zambrano, L.J., et al., *Applications of Machine Learning in Human Microbiome Studies: A Review on Feature Selection, Biomarker Identification, Disease Prediction and Treatment*. Front Microbiol, 2021. **12**: p. 634511.
4. Wang, F., et al., *Navigating the microarray landscape: a comprehensive review of feature selection techniques and their applications*. Front Big Data, 2025. **8**: p. 1624507.
5. A, A., *A Deep Learning Approach to Skin Cancer Detection in Dermoscopy Images*. J Biomed Phys Eng, 2020. **10**(6): p. 801-806.
6. Ahmadi Mehr, R. and A. Ameri, *Skin Cancer Detection Based on Deep Learning*. J Biomed Phys Eng, 2022. **12**(6): p. 559-568.
7. Ahmed, B., et al., *Malignant Melanoma: Skin Cancer-Diagnosis, Prevention, and TreatmentSkin Cancer Detection TechnologyUltraviolet Radiation Exposure and Its Impact on Skin Cancer Risk*. Crit Rev Eukaryot Gene Expr, 2020. **30**(4): p. 291-297.
8. Álvarez-Salafranca, M., et al., *Dermoscopy in Basal Cell Carcinoma: An Updated Review Development of a non-melanoma skin cancer detection modelArtificial Intelligence for Skin Cancer Detection: Scoping Review*. Actas Dermosifiliogr (Engl Ed), 2021. **112**(4): p. 330-338.
9. Arnold, M., et al., *Global Burden of Cutaneous Melanoma in 2020 and Projections to 2040*. JAMA Dermatol, 2022. **158**(5): p. 495-503.
10. Debelee, T.G., *Skin Lesion Classification and Detection Using Machine Learning Techniques: A Systematic Review*. Diagnostics (Basel), 2023. **13**(19).
11. Dildar, M., et al., *Skin Cancer Detection: A Review Using Deep Learning Techniques*. Int J Environ Res Public Health, 2021. **18**(10).
12. Aliero, M.S., et al., *Systematic Review Analysis on Smart Building: Challenges and Opportunities*. Sustainability, 2022. **14**(5).
13. Kitchenham, B., et al., *Systematic literature reviews in software engineering – A systematic literature review*. Information and Software Technology, 2009. **51**(1): p. 7-15.
14. *<Quality of Service Approaches in IoT - A Systematic Mapping.pdf>*.
15. Malekshahi Rad, M., et al., *Social Internet of Things: vision, challenges, and trends*. Human-centric Computing and Information Sciences, 2020. **10**(1).
16. Pérez-Lombard, L., J. Ortiz, and C. Pout, *A review on buildings energy consumption information*. Energy and Buildings, 2008. **40**(3): p. 394-398.
17. Aliero, M.S., et al., *Systematic Review Analysis on SQLIA Detection and Prevention Approaches*. Wireless Personal Communications, 2020.

10.48047/jocaaa.2025.34.12.14

18. Cavalcante, E., et al., *On the interplay of Internet of Things and Cloud Computing: A systematic mapping study.* Computer Communications, 2016. **89-90**: p. 17-33.
19. Zhu, Y., et al., *Macrophage autophagy deficiency-induced CEBPB accumulation alleviates atopic dermatitis via impairing M2 polarization SkinLiTE: Lightweight Supervised Contrastive Learning Model for Enhanced Skin Lesion Detection and Disease Typification in Dermoscopic Images A multimodal vision foundation model for clinical dermatology.* Cell Rep, 2023. **42**(11): p. 113430.
20. Zhou, L., et al., *Global, regional, and national trends in the burden of melanoma and non-melanoma skin cancer: insights from the global burden of disease study 1990-2021*. Sci Rep, 2025. **15**(1): p. 5996.
21. Zafar, M., et al., *Skin Lesion Analysis and Cancer Detection Based on Machine/Deep Learning Techniques: A Comprehensive Survey.* Life (Basel), 2023. **13**(1).
22. Y, B.V., et al., *Modified Le-Net Model with Multiple Image Features for Skin Cancer DetectionA multimodal vision foundation model for clinical dermatology.* Cancer Invest, 2025. **43**(7): p. 485-514.
23. Watson, M., D.M. Holman, and M. Maguire-Eisen, *Ultraviolet Radiation Exposure and Its Impact on Skin Cancer Risk*. Semin Oncol Nurs, 2016. **32**(3): p. 241-54.
24. Schadendorf, D., et al., *Melanoma A novel skin cancer detection model using modified finch deep CNN classifier model.* Lancet, 2018. **392**(10151): p. 971-984.
25. Rojas, K.D., et al., *Skin cancer: Primary, secondary, and tertiary prevention. Part II*

Skin cancer in skin of color Skin cancer--early detection. J Am Acad Dermatol, 2022. **87**(2): p. 271-288.

26. Rezk, E., M. Eltorki, and W. El-Dakhakhni, *Improving Skin Color Diversity in Cancer Detection: Deep Learning Approach*. JMIR Dermatol, 2022. **5**(3): p. e39143.
27. Reynaud, B., et al., *Multiple pigmented skin metastases of breast cancer mimicking cutaneous melanoma Developing skin cancer education materials for darker skin populations: crowdsourced design, message targeting, and acral lentiginous melanoma Burden of skin cancer in Colombia*. Ann Dermatol Venereol, 2022. **149**(3): p. 219-220.
28. Prelaj, A., et al., *Artificial intelligence for predictive biomarker discovery in immuno-oncology: a systematic review Improving Skin Color Diversity in Cancer Detection: Deep Learning Approach*. Ann Oncol, 2024. **35**(1): p. 29-65.
29. Nawaz, M., et al., *Skin cancer detection from dermoscopic images using deep learning and fuzzy k-means clustering*. Microsc Res Tech, 2022. **85**(1): p. 339-351.
30. Das, K., et al., *Machine Learning and Its Application in Skin Cancer.* Int J Environ Res Public Health, 2021. **18**(24).
31. Janda, M., et al., *Early detection of skin cancer in Australia - current approaches and new opportunities Skin Cancer Detection Using Deep Learning Approaches Artificial Intelligence for Skin Cancer Detection: Scoping Review.* Public Health Res Pract, 2022. **32**(1): p. 301-312.
32. Gordon, E.R., et al., *Ethical considerations for artificial intelligence in dermatology: a scoping review ArsenicNet: An efficient way of arsenic skin disease detection using enriched fusion Xception model.* Br J Dermatol, 2024. **190**(6): p. 789-797.
33. Gouda, W., et al., *Detection of Skin Cancer Based on Skin Lesion Images Using Deep Learning*. Healthcare (Basel), 2022. **10**(7).
34. Hammad, M., et al., *Enhanced Deep Learning Approach for Accurate Eczema and Psoriasis Skin Detection*. Sensors (Basel), 2023. **23**(16).

10.48047/jocaaa.2025.34.12.14

35. Li, Y.F., et al., *Caffeine Protects Skin from Oxidative Stress-Induced Senescence through the Activation of Autophagy.* Theranostics, 2018. **8**(20): p. 5713-5730.
36. Lin, P., et al., *Centella asiatica alleviates psoriasis through JAK/STAT3-mediated inflammation: An in vitro and in vivo study Detection algorithm for pigmented skin disease based on classifier-level and feature-level fusion.* J Ethnopharmacol, 2023. **317**: p. 116746.
37. Nigat, T.D., T.M. Sitote, and B.M. Gedefaw, *Fungal Skin Disease Classification Using the Convolutional Neural Network.* J Healthc Eng, 2023. **2023**: p. 6370416.
38. Kundu, S., et al., *Optimized Grasshopper Optimisation Algorithm enabled DETR (DEtection TRansformer) model for skin disease classification.* PLoS One, 2025. **20**(5): p. e0323920.
39. Wei, G., et al., *Patient and provider-directed adjunct diagnostic tools in the detection of skin cancer Skin cancer screening Skin cancer prevention.* Dermatol Online J, 2024. **30**(2): p. 99-114.
40. Freeman, S., et al., *Occupational skin disease Vesiculobullous skin disease with prominent immunologic feature Owner-reported flea treatment measures and skin disease in cats.* Curr Probl Dermatol, 1995. **22**(20): p. 80-5.
41. Bruch-Gerharz, D., T. Ruzicka, and V. Kolb-Bachofen, *Nitric oxide and its implications in skin homeostasis and disease - a review.* Arch Dermatol Res, 1998. **290**(12): p. 643-51.
42. Campos, L.C., et al., *Skin Manifestations in Adults With Chronic Granulomatous Disease in the United Kingdom Modelling skin disease: lessons from the worlds of mathematics, physics and computer science Skin manifestations of systemic autoimmune connective tissue disease: diagnostics and therapeutics Adipose-derived stem cells in immune-related skin disease: a review of current research and underlying mechanisms.* J Allergy Clin Immunol Pract, 2025. **13**(8): p. 2151-2161 e7.
43. Diotallevi, F., et al., *The Role of Nutrition in Immune-Mediated, Inflammatory Skin Disease: A Narrative Review.* Nutrients, 2022. **14**(3).
44. Shirley, S.N., A.E. Watson, and N. Yusuf, *Pathogenesis of Inflammation in Skin Disease: From Molecular Mechanisms to Pathology.* Int J Mol Sci, 2024. **25**(18).
45. Heibel, H.D., et al., *A Review of Noninvasive Techniques for Skin Cancer Detection in Dermatology Adjunctive Diagnostic Methods for Skin Cancer Detection: A Review of Electrical Impedance-Based Techniques Artificial intelligence in the detection of skin cancer: State of the art Skin cancer detection from dermoscopic images using deep learning and fuzzy k-means clustering Barriers to effective skin cancer detection Systematic review of approaches to detection and classification of skin cancer using artificial intelligence: Development and prospects Skin cancer detection through attention guided dual autoencoder approach with extreme learning machine.* Am J Clin Dermatol, 2020. **21**(4): p. 513-524.
46. Singal, A. and S.R. Lipner, *A review of skin disease in military soldiers: challenges and potential solutions.* Ann Med, 2023. **55**(2): p. 2267425.
47. O'Malley, J.T., et al., *Skin Inflammation in Human Health and Disease: 2018 International Conference Skin as a marker of general feline health: Cutaneous manifestations of systemic disease.* J Invest Dermatol, 2019. **139**(5): p. 991-994.