



**REVIEW**

# A Comprehensive Systematic Review: Advancements in Skin Cancer Classification and Segmentation Using the ISIC Dataset

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## ABSTRACT

The International Skin Imaging Collaboration (ISIC) datasets are pivotal resources for researchers in machine learning for medical image analysis, especially in skin cancer detection. These datasets contain tens of thousands of dermoscopic photographs, each accompanied by gold-standard lesion diagnosis metadata. Annual challenges associated with ISIC datasets have spurred significant advancements, with research papers reporting metrics surpassing those of human experts. Skin cancers are categorized into melanoma and non-melanoma types, with melanoma posing a greater threat due to its rapid potential for metastasis if left untreated. This paper aims to address challenges in skin cancer detection via visual inspection and manual examination of skin lesion images, processes historically known for their laboriousness. Despite notable advancements in machine learning and deep learning models, persistent challenges remain, largely due to the intricate nature of skin lesion images. We review research on convolutional neural networks (CNNs) in skin cancer classification and segmentation, identifying issues like data duplication and augmentation problems. We explore the efficacy of Vision Transformers (ViTs) in overcoming these challenges within ISIC dataset processing. ViTs leverage their capabilities to capture both global and local relationships within images, reducing data duplication and enhancing model generalization. Additionally, ViTs alleviate augmentation issues by effectively leveraging original data. Through a thorough examination of ViT-based methodologies, we illustrate their pivotal role in enhancing ISIC image classification and segmentation. This study offers valuable insights for researchers and practitioners looking to utilize ViTs for improved analysis of dermatological images. Furthermore, this paper emphasizes the crucial role of mathematical and computational modeling processes in advancing skin cancer detection methodologies, highlighting their significance in improving algorithmic performance and interpretability.

## KEYWORDS

Medical image; skin cancer classification; skin cancer segmentation; international skin imaging collaboration; convolutional neural network; deep learning



## 1 Introduction

As per the World Health Organization (WHO), cancer stands out as a leading cause of death [1]. Statistical analyses reveal a concerning trend, with over two individuals succumbing to skin cancer every hour in the United States alone. The incidence of various skin cancer types has witnessed a rise over the past decade, with approximately 3 million non-melanoma skin cancer cases and 132,000 melanoma skin cancer cases diagnosed globally each year [2]. The primary factors contributing to skin cancer include UV radiation, genetic predisposition, unhealthy lifestyle choices, and smoking. UV radiation is singled out as the predominant cause, and the swift depletion of ozone layers exacerbates the issue by allowing more harmful UV radiation to reach the Earth's surface. Consequently, an upsurge in skin cancer cases is anticipated [3]. Early detection of skin cancer holds immense importance, offering heightened chances of successful treatment and prevention of metastasis to other organs. Dermoscopy, a noninvasive technique for examining pigmented skin lesions at the surface level, proves valuable for early diagnosis. Despite this, early detection remains a formidable task, even for seasoned dermatologists, owing to the diverse manifestations of skin cancer. Challenges arise from deciphering whether a manifestation like swelling is benign or malignant. Furthermore, the inconspicuous nature of small forms, such as moles, makes detection difficult with the naked eye. Therefore, there is a pressing need for more precise and reliable detection methods.

As per data provided by the WSRF for the year 2020 [4], Australia exhibited the highest incidence rate, recording an estimated 161,171 new cases. New Zealand reported 2801 cases, while Denmark, Netherlands, Norway, Sweden, Switzerland, Germany, Slovenia, and Finland each had fewer than 10,000 new cases. Fig. 1 visually represents the global skin cancer index. Skin cancer affects both men and women on a global scale, with men accounting for 173,844 new cases and women for 150,791 new cases. In terms of male incidence rates, Australia led with an estimated 9462 new cases, followed by Germany with 17,260 cases. New Zealand, Denmark, Netherlands, Norway, Sweden, Slovenia, Switzerland, and Finland each reported fewer than 5000 cases. For women, Slovenia reported the highest incidence rate of melanoma skin cancer, with approximately 14,208 new cases, followed by Norway with 3890 cases. New Zealand, Sweden, Switzerland, Denmark, Germany, Netherlands, and Finland each reported fewer than 3000 new cases. The data provided by WCRF highlights the global distribution of melanoma skin cancer cases and the varying incidence rates across different countries [5].

Section 1 serves as the introduction, setting the stage by introducing the ISIC dataset and its pivotal role in collaborative efforts for skin cancer analysis. In Section 2, a concise overview of skin cancer classification and segmentation utilizing the ISIC dataset is presented, providing readers with foundational knowledge. The methodology employed in these processes is detailed in Section 3. Section 3 delves into the dataset's characteristics, offering insights into its composition and complexities. Challenges such as data quality and labeling accuracy are thoroughly discussed in Section 4, alongside proposed solutions. Section 5 explores future directions for advancing skin cancer diagnostics. The paper concludes in Section 6, summarizing findings and highlighting the significant contributions of vision transformers in enhancing skin cancer analysis using the ISIC dataset. This structured approach efficiently guides researchers and clinicians through the dataset introduction, challenges, and future directions in skin cancer diagnostics. Fig. 2 presents the overall layout of the survey paper.

This structured approach aims to efficiently guide researchers and clinicians through dataset introduction, challenges, and future directions in advancing skin cancer diagnostics.

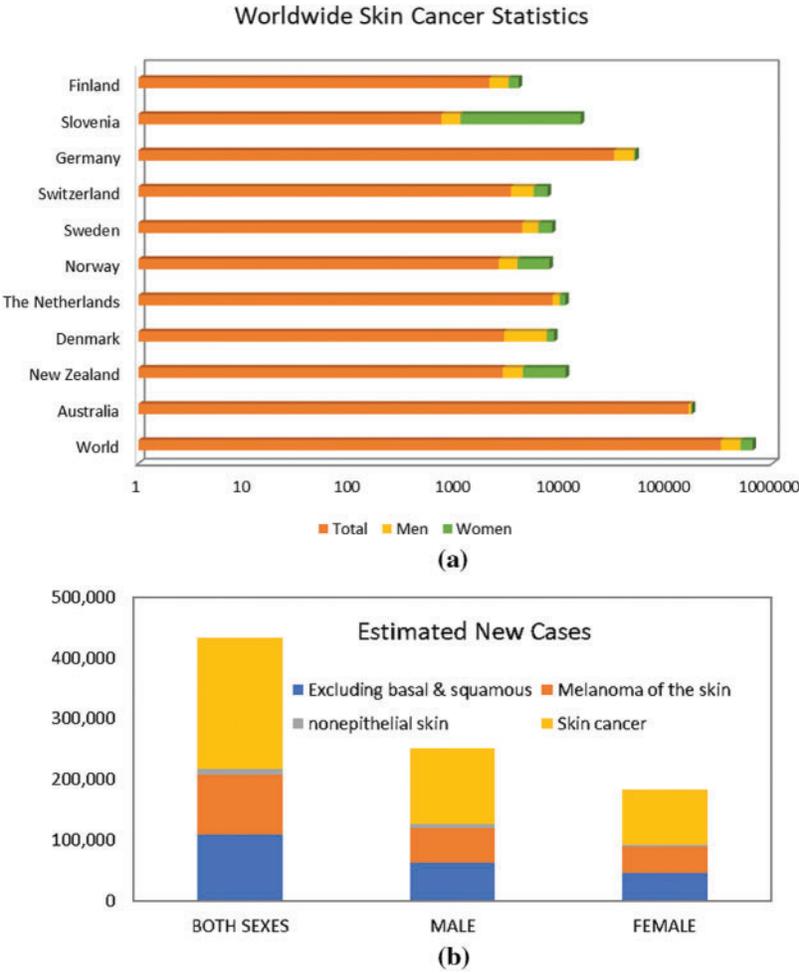


Figure 1: Worldwide skin cancer statistics



Figure 2: Layout of survey paper on ISIC dataset

The significance of mathematical and computational modeling processes cannot be overstated. This paper emphasizes their pivotal role, particularly in advancing methodologies for skin cancer detection. It underscores the crucial intersection between computer science and mathematical modeling, illustrating how these disciplines collaborate to improve algorithmic performance and interpretability. In [Section 4](#), the paper delves into the intricate mathematical equations that underpin the algorithms utilized in the ISIC, SCC, and SCS tasks. Detailed discussions on the mathematical modeling processes are provided for well-established architectures such as VGG-16, ResNet50, AlexNet, and ShuffleNet within the context of SCC. Additionally, comprehensive explanations of the mathematical equations governing the operation of advanced segmentation architectures, including U-Net and SegNet, are meticulously outlined. This rigorous examination illuminates the computational and mathematical foundations of these algorithms, enriching our understanding of their functioning and facilitating their application in dermatological image analysis using the ISIC dataset. All abbreviations are presented in [Table 1](#).

**Table 1:** Abbreviations

Abbreviation	Definition
WHO	World Health Organization
ISIC	International skin imaging collaboration
BCC	Basal cell carcinoma
SCC	Squamous cell carcinoma
AKs	Actinic keratoses
VGG	Visual geometry group
LSVRC	Large scale visual recognition challenge
UV	Ultraviolet
CNN	Convolutional neural networks
SCC	Skin cancer classification
SCS	Skin cancer segmentation
MRI	Magnetic resonance imaging
CT	Computed tomography
WSRF	World cancer research funds
SVM	Support vector machine
BYOL	Bootstrap your own latent

## 2 Literature Review

This section provides a comprehensive overview of the application of medical datasets, specifically focusing on the widely acclaimed ISIC image datasets. It delves into crucial issues pertinent to their utilization, encompassing concerns such as the prevalence of duplicate images, class imbalances, variations in image resolution, and potential label inaccuracies. Moreover, it emphasizes the primary focus of this paper, which is centered around SCC and SCS utilizing the ISIC dataset. By synthesizing these observations, this paper underscores the pivotal role of CNNs as formidable tools in the realm of dermatology, offering promising avenues for advancing clinical decision-making processes. Furthermore, it underscores the significance of leveraging the ISIC dataset as a cornerstone in

the pursuit of enhancing skin cancer diagnosis and treatment through innovative machine-learning methodologies.

The primary method for diagnosing skin cancer is visual examinations by dermatologists, which demonstrate an accuracy of approximately 60%. Dermoscopy, an enhanced imaging technique, increases diagnostic accuracy to 89%. Dermoscopy also exhibits specific sensitivity rates, such as 82.6% for melanocytic lesions, 98.6% for basal cell carcinoma, and 86.5% for squamous cell carcinoma [6]. Despite its effectiveness, dermoscopy faces challenges in accurately diagnosing certain lesions, especially early melanomas lacking distinct features. While it significantly improves melanoma diagnosis, there remains a need to enhance accuracy, particularly for featureless melanomas, to further improve patient survival rates. The limitations of dermoscopy and the quest for higher diagnostic accuracy have led to the development of computer-aided detection methods for skin cancer diagnosis [7].

The utilization of ISIC datasets is diverse, with a predominant focus on classification and segmentation tasks. Binary classification tasks have garnered significant attention, given their capacity to offer a larger pool of images for algorithm training. The advent of ISIC 2018 and ISIC 2019 marked a shift towards exploring multiclass classification, primarily leveraging the ISIC 2020 dataset. It is noteworthy that the ISIC 2020 challenge centered specifically on melanoma detection, indicating a potential surge in additional binary classification studies in subsequent research. While segmentation tasks have not gained as much popularity as lesion diagnosis, especially beyond 2019 when ISIC discontinued this challenge type, the ISIC 2016 to 2018 datasets stand out for providing delineated segmentation masks. However, the number of segmentation tasks is relatively limited compared to the abundance found in classification tasks [8].

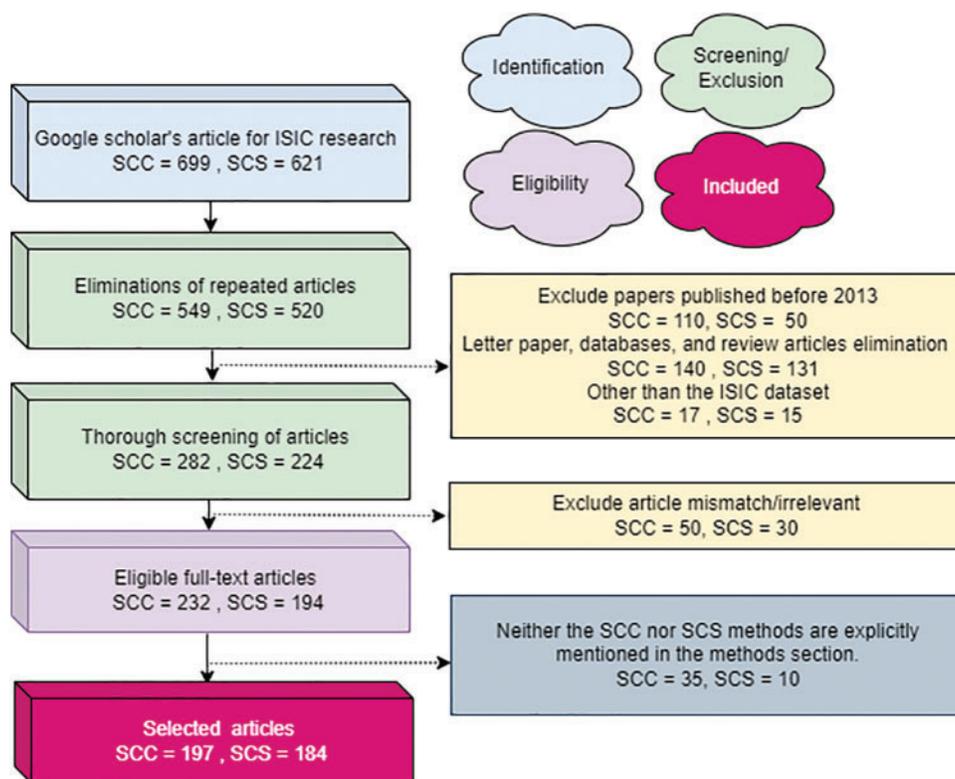
Beyond classification and segmentation, researchers have delved into other dimensions of ISIC datasets. For instance, a study by [9] investigated the impact of color constancy, while reference [10] explored data augmentation using generative adversarial networks. These diverse applications highlight the versatility of ISIC datasets for addressing various aspects of skin image analysis beyond traditional classification and segmentation tasks [11]. The utilization of the ISIC dataset has significantly propelled the field of skin cancer analysis, particularly in the realms of classification and segmentation. The dataset's richness and diversity have enabled researchers to explore and implement state-of-the-art techniques, leveraging advanced machine learning algorithms and deep neural networks. The collective efforts within the research community, as showcased in this paper, underscore the dataset's pivotal role in enhancing diagnostic precision and efficacy. Through a synthesis of the latest developments and strategies, this study strives to not only provide a comprehensive overview but also to equip researchers and clinicians with the necessary insights to navigate the complexities of skin cancer analysis. By delving into the intricacies of image segmentation methodologies and the nuanced landscape of classification techniques, this paper seeks to foster a deeper understanding of the ISIC dataset's potential, fostering advancements that hold promise for more accurate, reliable, and clinically relevant outcomes in the diagnosis and treatment of skin cancer [12].

In recent times, advancements in deep learning techniques within artificial intelligence have led to the development of novel solutions for detecting abnormalities across various medical domains, including breast cancer, lung cancer, skin cancer, brain tumors, liver cancer, and colon cancer, utilizing medical imaging technologies. CNNs have emerged as pivotal tools, particularly in image processing applications such as CT, MRI, histology images, and pathology images, among others, owing to their remarkable performance. In dermatology, CNNs have demonstrated significant potential in assisting physicians with the diagnosis of SCC and SCS.

### 3 Methods

#### 3.1 Systematic Review

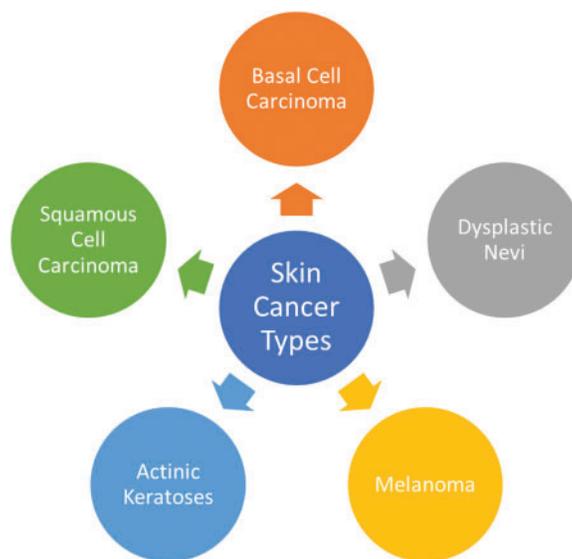
This review employs the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) strategy for article selection. Using a Google Scholar search with the keywords “skin cancer classification” and “skin cancer segmentation,” 699 SCC and 621 SCS publications were initially identified. After removing duplicates, there are 549 SCC and 520 SCS articles. The first screening round, excluding the ISIC dataset and those categorized as reviews, database entries, or letters, results in 282 SCC and 224 SCS articles from 2013 to 2023. Further exclusions are made based on relevance to the review’s objectives and suitability of schemes, leaving 232 SCC and 194 SCS articles. Subsequently, articles not explicitly illustrating SC and SCC systems or similar strategies are deleted, reducing the count to 197 SCC and 184 SCS articles. Fig. 2 presents the overall structure of paper and Fig. 3 demonstrates the PRISMA process extensively.



**Figure 3:** The PRISMA process utilized for articles entails detailing the criteria for inclusion and exclusion of evidence within the article

#### 3.2 Skin Cancer Types

This section provides an in-depth overview of the most prevalent forms of skin cancers, exploring their characteristics, impact on individuals, and the role of datasets like ISIC in enhancing research and diagnosis. Fig. 4 presents the graphical view of all skin cancer types.



**Figure 4:** Most common skin cancer types

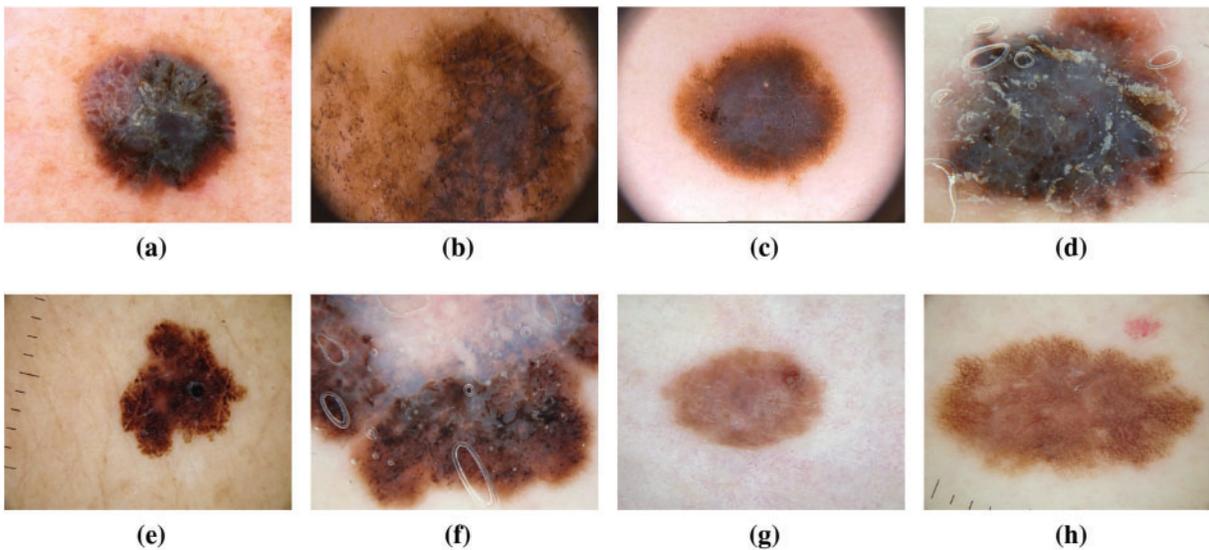
### 3.2.1 Melanoma

Melanoma, often referred to as “the most serious skin cancer,” is notorious for its potential to metastasize throughout the body. It can arise in normal, healthy skin or develop within existing moles [13,14]. Men are prone to developing melanoma on their faces or trunks, with occurrences even in sun-protected skin for both genders [15]. Early detection is paramount, and the ISIC dataset has played a pivotal role in advancing research for the timely identification and treatment of melanoma. Studies leveraging the dataset have contributed to improving diagnostic accuracy and enhancing our understanding of melanoma’s diverse manifestations [16]. Recent investigations utilizing the ISIC dataset have delved into molecular markers associated with melanoma progression, shedding light on potential therapeutic targets for personalized treatment strategies [17]. Moreover, advancements in machine learning algorithms, fueled by the wealth of data in the ISIC dataset, have enabled the development of predictive models for melanoma prognosis [18]. These models not only aid in risk stratification but also contribute to optimizing treatment plans for affected individuals. The collaborative nature of data sharing within the ISIC community has fostered a global exchange of insights, accelerating the pace of melanoma research and paving the way for innovative approaches in precision medicine [19]. Fig. 5 has an image annotation of melanoma.

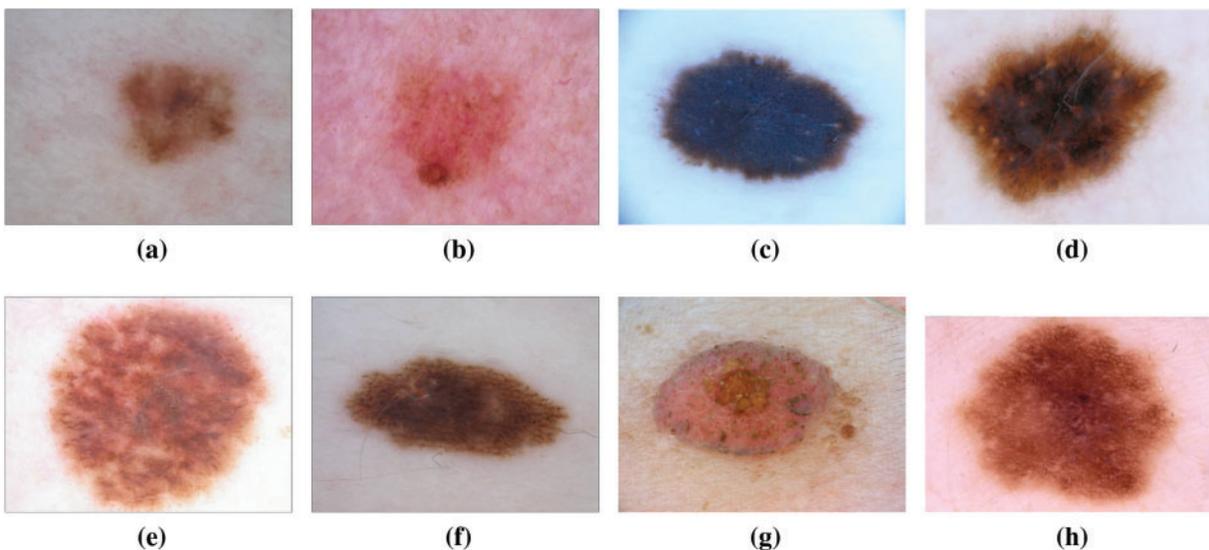
### 3.2.2 Dysplastic Nevi

Dysplastic nevi, recognized as atypical moles, exhibit characteristics resembling normal moles but possess melanoma-like traits. With irregular shapes or colors and larger sizes than typical moles, they can emerge on various skin areas, including those typically covered or exposed to the sun. The ISIC dataset has been instrumental in studying and classifying dysplastic nevi, aiding researchers in identifying patterns and features associated with their progression towards malignancy [20,21]. In recent years, the wealth of data within the ISIC dataset has facilitated in-depth analyses exploring the genetic markers linked to dysplastic nevi. This has not only refined our understanding of the molecular underpinnings of atypical moles but has also contributed to the development of more accurate diagnostic tools [22]. Machine learning models trained on the ISIC dataset have showcased

promising capabilities in distinguishing between benign and potentially malignant nevi, providing clinicians with valuable insights for early intervention [23]. Moreover, collaborative efforts within the dermatology community, fueled by the shared ISIC dataset, have led to the identification of novel biomarkers associated with dysplastic nevi progression [24]. This collaborative approach has fostered a collective understanding of atypical mole biology, paving the way for more targeted and effective strategies in the prevention and early detection of melanoma. The ISIC dataset continues to be a cornerstone in ongoing research endeavors focused on unraveling the complexities of dysplastic nevi, guiding advancements in both clinical practice and scientific understanding [25]. Fig. 6 has an image annotation of dysplastic nevi.



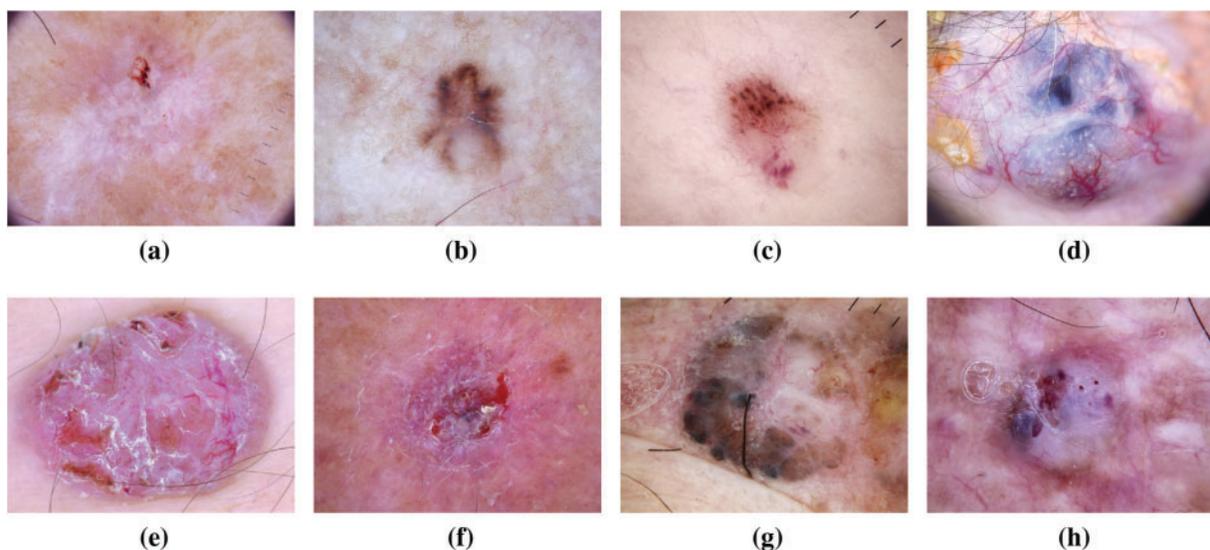
**Figure 5:** From (a) to (h): different states of Melanoma images of ISIC dataset



**Figure 6:** From (a) to (h): different states of Dysplastic Nevi images of ISIC dataset

### 3.2.3 Basal Cell Carcinoma

As the most prevalent form of skin cancer, BCC often manifests as a flesh-colored growth, a pearl-shaped bump, or a pinkish skin patch. Linked to prolonged indoor tanning or frequent sun exposure, it primarily affects individuals with fair skin but can also impact those with darker skin tones [26]. The ISIC dataset has significantly contributed to BCC research, providing a wealth of diverse images for analysis. This dataset has been instrumental in developing and validating machine learning models for early detection, preventing the spread of BCC and associated complications [27,28]. Recent studies leveraging the ISIC dataset have explored the molecular signatures associated with different subtypes of BCC. This deeper understanding has not only refined diagnostic accuracy but has also paved the way for targeted therapeutic interventions [29]. Additionally, the diverse representation of BCC cases in the ISIC dataset has facilitated the development of robust classification algorithms capable of distinguishing BCC from other skin lesions with high precision [30]. Fig. 7 has an image annotation of BCC. Furthermore, collaborative initiatives fueled by the ISIC dataset have allowed researchers to investigate the impact of environmental factors on BCC development, providing insights into potential preventive measures [31]. The shared dataset has acted as a catalyst for international collaboration, fostering a collective effort to mitigate the impact of BCC on public health. As a result, the ISIC dataset stands as a cornerstone in ongoing efforts to advance our understanding of BCC, with implications for improved diagnosis, treatment, and prevention strategies [32].

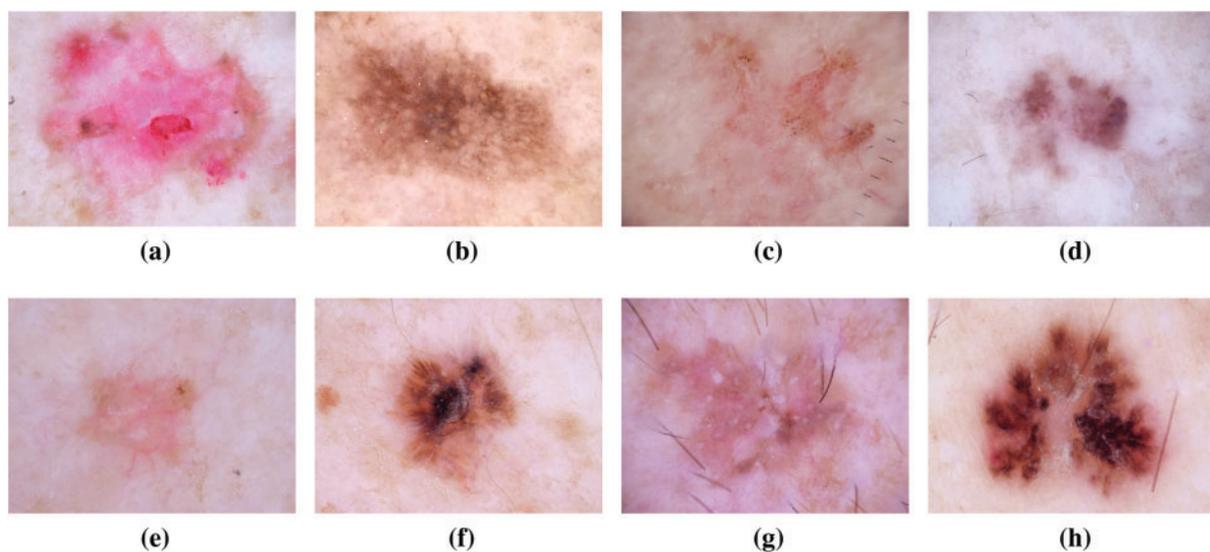


**Figure 7:** From (a) to (h): different states of Basal Cell Carcinoma images of ISIC dataset

### 3.2.4 Squamous Cell Carcinoma

SCC, a common skin cancer type, is more prevalent in individuals with light skin, although it can affect individuals with darker skin tones. It often presents as a red, firm lump, a scaly area, or a recurrent sore [33,34]. Frequent sun-exposed areas are susceptible to SCC development. Research leveraging the ISIC dataset has facilitated the exploration of unique patterns and features associated with SCC. The dataset's contribution has led to advancements in early detection techniques and the development of targeted treatment approaches [35]. Recent investigations using the ISIC dataset have focused on unraveling the genomic landscape of SCC, providing insights into the molecular

mechanisms driving its development and progression [36]. This deeper understanding has paved the way for personalized treatment strategies, potentially improving outcomes for individuals diagnosed with SCC. Additionally, machine learning applications trained on the ISIC dataset have demonstrated promising capabilities in distinguishing between different subtypes of SCC, aiding clinicians in refining their diagnostic assessments [37]. Furthermore, collaborative efforts within the dermatology research community, fueled by the ISIC dataset, have facilitated international studies on the epidemiology of SCC [38]. This collective approach has not only enhanced our understanding of risk factors associated with SCC but has also informed public health strategies for prevention and early intervention. The ongoing contributions of the ISIC dataset continue to play a crucial role in advancing SCC research, with implications for improved diagnostics, treatment outcomes, and public health policies. Fig. 8 has an image annotation of SSC.

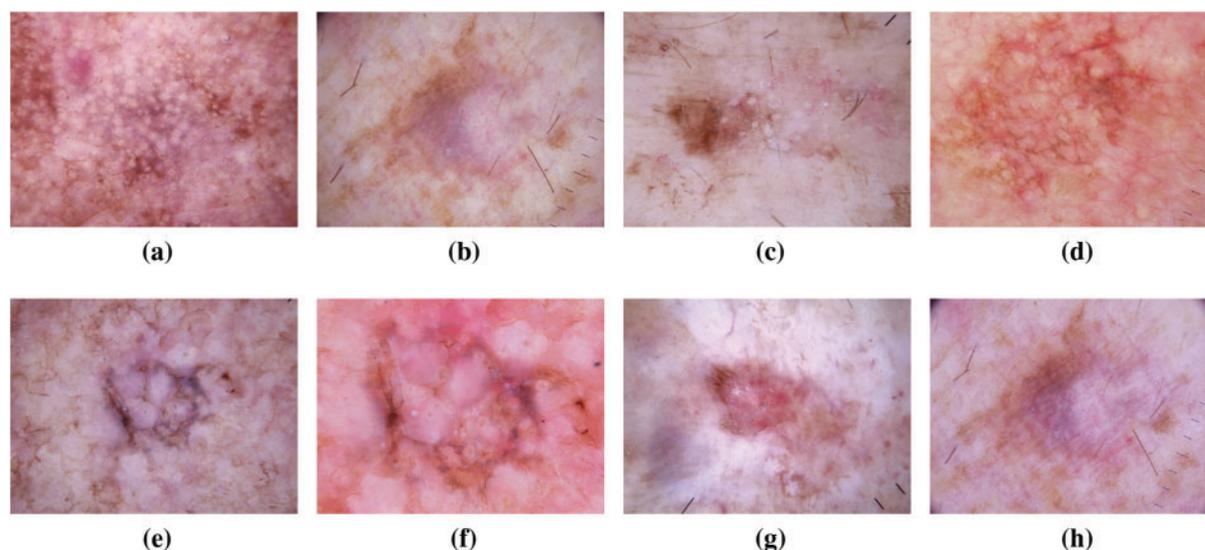


**Figure 8:** From (a) to (h): different stages of Squamous Cell Carcinoma images of ISIC dataset

### 3.2.5 Actinic Keratoses

While not categorized as skin cancer, AKs are precursors with the potential to progress into squamous cell carcinoma. These scaly, dry skin lesions result from excessive sun exposure and typically appear on the head, neck, hands, and forearms. The ISIC dataset has been crucial in studying the evolution of AKs, aiding in distinguishing benign lesions from those with malignant potential. Insights from the dataset have informed timely interventions to prevent the progression of AKs into advanced stages of skin cancer [39]. Recent analyses leveraging the extensive data within the ISIC dataset have provided a deeper understanding of the genetic and molecular alterations associated with AKs. This knowledge has not only refined diagnostic criteria but has also contributed to the identification of biomarkers indicative of malignant transformation. Machine learning applications trained on the ISIC dataset have demonstrated promising capabilities in predicting the likelihood of AKs advancing to squamous cell carcinoma, allowing for more personalized and proactive patient management [40,41]. Fig. 9 has an image annotation of AKs. Moreover, collaborative efforts among dermatologists and researchers, facilitated by the shared ISIC dataset, have enabled the development of risk stratification models for individuals with AKs. These models consider a range of factors, including clinical features and genetic markers, to tailor surveillance and intervention strategies. The global exchange of insights

within the ISIC community has played a pivotal role in shaping guidelines for the management of AKs, emphasizing the importance of preventive measures and early interventions to mitigate the risk of progression to invasive skin cancer [42]. Where Table 2 presents the characteristics and ISIC data contribution for different skin cancer types.



**Figure 9:** From (a) to (h): various states of Actinic Keratoses images of ISIC dataset

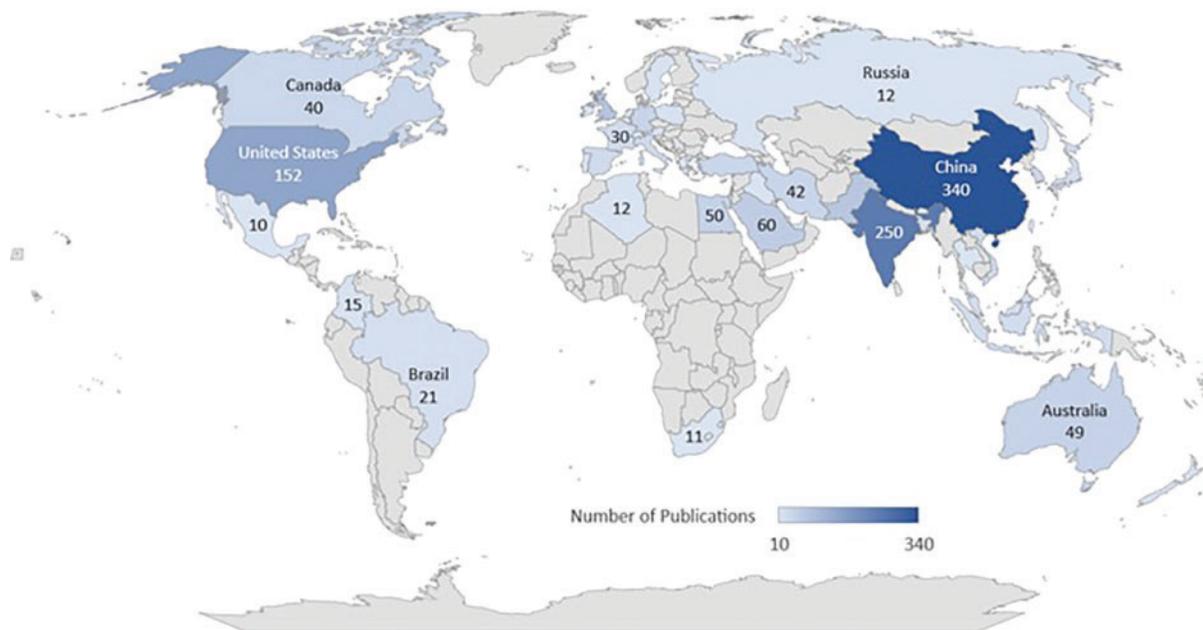
**Table 2:** Characteristics and ISIC dataset contribution for different skin cancer types

Skin cancer type	Characteristics	ISIC dataset contribution
Melanoma	Asymmetrical, irregular borders, multicolored	Advanced diagnostic models, nuanced lesion analysis
Dysplastic Nevi	Irregular borders, uneven coloring, larger diameter	Key features identification, aiding in differentiation
Basal Cell Carcinoma	Pearly or waxy bump, visible blood vessels	Refinement of diagnostic models, early detection
Squamous Cell Carcinoma	Scaly, red patch, firm lump	Identification of unique visual cues, enhanced accuracy
Actinic Keratoses	Dry, scaly patches from sun damage	Contribution to AK research, distinguishing malignant potential

Skin cancer symptoms encompass changes in moles, the appearance of new lesions, or alterations in skin texture. Early detection is crucial, prompting regular self-examination and professional checks. Precautions include sun safety practices wearing protective clothing, using sunscreen, and avoiding excessive sun exposure [43]. Prevalence varies among skin cancer types. BCC is most common, linked to sun exposure. SCC follows, associated with sun exposure and tobacco use. Melanoma, the most serious type, requires vigilance for changes in moles. Dysplastic nevi, atypical moles, necessitate close monitoring: AKs, precursors to SCC, mandate sun protection [44]. While BCC has a higher patient prevalence due to sun exposure, early detection, and preventive measures are universally vital. Regular

skin checks and adherence to sun safety mitigate risks across all skin cancer types. Individuals need to be proactive in monitoring their skin, seeking professional evaluation for any concerning changes, and adopting sun-safe behaviors to reduce the overall burden of skin cancer [45]. Public awareness campaigns play a pivotal role in educating individuals about skin cancer symptoms, the importance of early detection, and the significance of sun protection. Dermatologists emphasize the need for routine skin examinations, especially for those with fair skin or a history of sun exposure. With advancements in technology, mobile applications, and telemedicine services are also becoming valuable tools for promoting skin health and providing accessible avenues for skin cancer assessments. Regular check-ups with healthcare providers further enhance the collective effort in preventing, detecting, and managing skin cancer, ultimately contributing to improved outcomes and reduced morbidity [46].

Fig. 4 illustrates common types of skin cancers, emphasizing the diverse visual representations captured in the ISIC dataset that contribute to a deeper understanding of each skin cancer type. Fig. 10 presents the incidence of skin cancer across different regions over the past years.



**Figure 10:** Worldwide publication on skin cancer images using ISIC dataset

### 3.3 ISIC Dataset

Our research delved into the utilization of ISIC datasets for various research objectives, spanning the past 4 to 5 years. Due to the widespread adoption of ISIC datasets, offering a comprehensive list of studies is unfeasible. Nevertheless, we meticulously selected some of the most prominent and well-cited papers for our analysis. Our examination revealed a prevalent trend where recent research often incorporated multiple datasets, showcasing the versatile nature of ISIC datasets. The ISIC dataset has evolved significantly over the years, starting with ISIC 2016, comprising 900 training images and 379 test images, totaling 1279 images. Each image was sized at  $512 \times 512$  pixels and included ground truth data indicating lesion malignancy. Subsequent years saw substantial expansions: ISIC 2017 contained 2600 images; ISIC 2018 introduced a dataset with 10,015 training images and 1512 test images, totaling 11,527 images at  $600 \times 450$  pixels. The trend continued with ISIC 2019, offering 25,331 training images

and 8238 test images, totaling 33,569 images at  $1024 \times 1024$  pixels. In 2020, the largest ISIC dataset yet was released, comprising 33,126 training images and 10,982 test images, totaling 44,108 images with varying resolutions, commonly at  $768 \times 786$  pixels.

Our analysis highlighted the predominant focus on tasks such as classification and segmentation within the studies deemed relevant. Binary classification emerged as a popular research area, particularly with the advent of ISIC 2018 and ISIC 2019 datasets. Moreover, the ISIC 2020 challenge specifically concentrated on melanoma detection, potentially leading to an influx of additional binary classification papers. While SCS tasks are not as prevalent as cancer diagnosis, ISIC datasets, particularly ISIC 2016 to 2018, provided valuable delineated segmentation masks. Additionally, other notable applications of ISIC datasets include studies on color constancy impact and data augmentation using generative adversarial networks. Table 3 presents the annotation of ISIC dataset in various publications.

**Table 3:** Characteristics of ISIC in various publications

Publication	Datasets	Images	DA	Method
Hekler et al. [47]	HAM10000, ISIC	804	No	Binary classification
Rotemberg et al. [48]	ISIC 2020	33,126	No	Binary classification
Bisla et al. [49]	ISIC 2017, ISIC 2018, PH2, Dermofit	1875	Yes	Binary classification
Bissoto et al. [50]	Atlas, ISIC 2018	3466	Yes	Binary classification
Xie et al. [51]	ISIC 2017/2018	6344	Yes	Segmentation
Jojoa Acosta et al. [52]	ISIC 2017, PH2 malignant	2742	Yes	Binary classification
Adegun et al. [53]	ISIC 2017, PH2	2860	Yes	Binary classification
Nahata et al. [54]	ISIC 2018/2019	35,348	Yes	Binary classification
Ha et al. [55]	ISIC 2018, ISIC 2019, ISIC 2020	33,000+	Yes	Binary classification (with 9-class output)
Goyal et al. [56]	ISIC 2017, PH2	3520	Yes	Segmentation
Brinker et al. [57]	ISIC 2016, HAM10000	12,378	No	Binary classification
Mahbod et al. [58]	ISIC 2016/2017	2787	Yes	Binary classification + seborrheic keratosis
Bisla et al. [59]	ISIC 2017/2018, Dermofit, PH2	16,270	Yes	Generative adversarial network segmentation and binary classification
Tang et al. [60]	ISIC 2016/2017, PH2	4079	Yes	Segmentation
Majtner et al. [61]	ISIC 2016	1279	No	Binary classification
Barbosa et al. [62]	ISIC 2017	2750	Yes	Binary classification
Gessert et al. [63]	ISIC 2018	13,500	Yes	Multi-class (7 classes)
Al-Antari et al. [64]	ISIC 2018	11,720	Yes	Multi-class (7 classes)

### ***3.4 Overview of SCC and SCS with ISIC Dataset***

The ISIC dataset has emerged as a pivotal resource in advancing research on skin cancer detection and segmentation. Skin cancer, one of the most prevalent types of cancer, necessitates early and accurate diagnosis for effective treatment. The ISIC dataset addresses this imperative by providing a comprehensive collection of high-resolution dermoscopic images, encompassing various skin lesions, including malignant and benign cases [65]. Skin cancer classification involves the categorization of lesions into different classes, such as melanoma, basal cell carcinoma, and squamous cell carcinoma. Machine learning and deep learning techniques have been extensively applied to the ISIC dataset for automated classification, leveraging the rich visual information present in dermoscopic images [66]. CNNs and other deep learning architectures have demonstrated remarkable performance in distinguishing between different skin lesions with a high degree of accuracy [67]. In addition to SCC, SCS plays a crucial role in delineating the boundaries of skin lesions, aiding in a more detailed analysis of their characteristics. Segmentation algorithms applied to the ISIC dataset aim to precisely identify and outline the regions of interest within the images, facilitating a better understanding of lesion morphology and size [68]. Researchers often employ transfer learning, fine-tuning pre-trained models, and ensemble techniques to enhance the generalization and robustness of skin cancer classification and segmentation models. The ISIC dataset's large-scale and diverse collection of images contributes to the development of robust models that can handle variations in skin types, lesion sizes, and imaging conditions [69].

As the field continues to evolve, collaborations like ISIC play a pivotal role in fostering advancements in skin cancer research. The integration of advanced computer vision techniques with the rich data provided by the ISIC dataset holds promising potential for improving early detection and aiding clinicians in making more informed decisions for optimal patient care [70,71]. Furthermore, the ISIC dataset supports benchmarking and comparison of different algorithms, fostering healthy competition and driving innovation in the field of dermatology [72]. The incorporation of clinical metadata, such as patient demographics and lesion histories, enhances the dataset's utility for building models that not only classify and segment lesions but also consider the broader patient context [73].

The ISIC dataset's global accessibility has facilitated collaborative efforts across institutions, enabling researchers worldwide to contribute to the collective knowledge in skin cancer research [74]. Open challenges and competitions based on the ISIC dataset serve as platforms for researchers to showcase novel approaches and methodologies, fostering a community-driven pursuit of improved diagnostic tools [75]. Ethical considerations and privacy concerns in handling medical image datasets, including the ISIC dataset, have prompted the development of secure and privacy-preserving methodologies [76]. Researchers are increasingly mindful of ensuring patient privacy and obtaining proper consent, laying the foundation for responsible and transparent use of medical data.

Continuous updates and expansions of the ISIC dataset, incorporating new cases and diverse populations, ensure that the models trained on this dataset remain relevant and applicable across different scenarios [77]. The evolving nature of skin cancer pathology demands a dynamic dataset, and the ISIC collaboration is responsive to this need [78]. In response to emerging challenges, such as data scarcity in specific subtypes or demographic groups, efforts are underway to enhance the representatives of the ISIC dataset. This includes targeted data collection initiatives and collaborations with diverse healthcare institutions to ensure a more comprehensive and inclusive dataset that can address disparities in skin cancer diagnosis and treatment [79]. The ongoing integration of multi-modal data, including not only dermoscopic images but also clinical and genetic information, further enriches

the ISIC dataset. Fig. 11 presents the number of ISIC images used in the various publications for the skin cancer SCC and SCS.

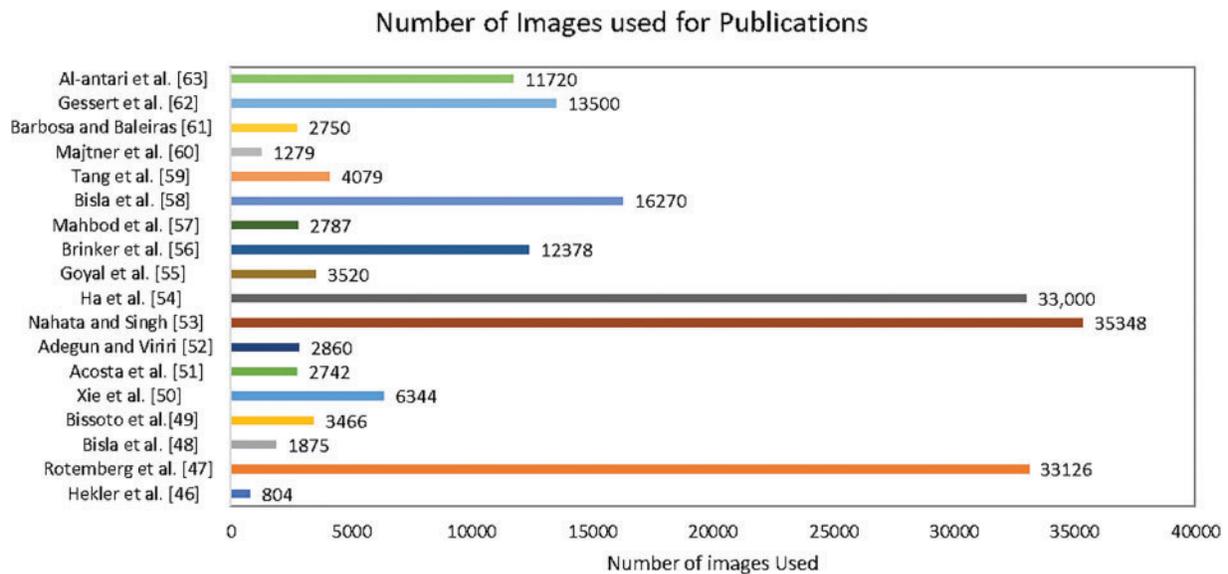


Figure 11: Number of images used in various publications

This holistic approach facilitates a more comprehensive understanding of skin cancer, enabling researchers to explore correlations between genetic markers, clinical parameters, and imaging features for a more nuanced diagnosis and prognosis [80]. As artificial intelligence applications in dermatology continue to evolve, there is a growing emphasis on the interpretability and explainability of models trained on the ISIC dataset. Transparent models can enhance trust among healthcare practitioners, fostering seamless integration of AI-driven tools into clinical workflows for more effective decision-making [81]. Moreover, the dynamic nature of the ISIC dataset not only fosters advancements in algorithmic precision but also encourages ongoing research into emerging skin cancer subtypes and their distinct diagnostic markers. This adaptability ensures that the dataset stays abreast of the ever-evolving landscape of dermatological knowledge, contributing to the refinement of diagnostic methodologies [82]. Additionally, the ISIC dataset’s open-access nature cultivates a global community of researchers, allowing for the seamless exchange of ideas, methodologies, and benchmarking standards. This collaborative ethos promotes a collective push towards more accurate, efficient, and universally applicable skin cancer diagnostic tools, ultimately benefiting patients worldwide [83]. Table 4 demonstrates the contribution of ISIC dataset in skin cancer types.

Table 4: Literature review of ISIC dataset contribution for different skin cancer types

Authors	Dataset	Model	Performance
Gajera et al. [84]	ISIC 2016, ISIC 2017	AlexNet, VGG-16, VGG-19	Accuracy = 98.33%, F1-score = 0.96
Shinde et al. [85]	ISIC	Squeeze-MNet	Accuracy = 99.36%
Alenezi et al. [86]	ISIC 2017	Deep residual network	Accuracy = 96.971%, F1-score = 0.95

(Continued)

**Table 4 (continued)**

Authors	Dataset	Model	Performance
Alenezi et al. [87]	ISIC 2019, ISIC 2020	ResNet-101 with SVM	Accuracy = 96.15% (2019), 97.15% (2020)
Gouda et al. [88]	ISIC 2018	CNN	Accuracy = 83.2%
Bassel et al. [89]	ISIC	ResNet50, Xception, VGG-16	Accuracy = 90.9%, F1-score = 0.89
Kousis et al. [90]	ISIC 2019	Eleven CNN architectures with DensNet169	Accuracy = 92.25%, F1-score = 0.932
Shorfuzzaman [91]	ISIC archive	DenseNet121, Xception, EfficientNet80	Accuracy = 95.76%, F1-score = 0.957
Abbas et al. [92]	ISIC 2020	NASNet	Accuracy = 97.7%, F1-score = 0.97
Reis et al. [93]	ISIC 2018, ISIC 2019, ISIC 2020	InSiNet, U-Net	Accuracy = 94.59% (2018), 91.89% (2019), 90.54% (2020)
Ghosh et al. [94]	ISIC archive	SkinNet-16	Accuracy = 95.51% (HAM10000), 99.19% (ISIC)
Mazoure et al. [95]	ISIC	Inceptionv313, ResNet5014, 170 MobileNetv23, EfficientNet15, BYOL16, SwAV	Class prediction probability = 1.00 (Mel)
Rashid et al. [96]	ISIC 2020	MobileNetV2-based transfer learning	Average accuracy = 98.20%
Aljohani et al. [97]	ISIC 2019	DenseNet201, MobileNetV2, ResNet50V2, ResNet152V2, Xception, VGG-16, VGG-19, GoogleNet	Accuracy = 76.09%
Demir et al. [98]	ISIC archive	ResNet-101, Inception-v3	F1-score = 84.09% (ResNet-101), 87.42% (Inception-v3)
Khan et al. [99]	ISIC 2017, ISIC 2019	A hybrid framework of 20 layered and 17 layered CNN for segmentation, 30 layered CNN for feature extraction	Segmentation accuracy = 92.70% (ISIC 2018), Classification accuracy = 87.02%
Abdar et al. [100]	ISIC 2019	ResNet152V2, MobileNetV2, DenseNet20	Best accuracy = 89%, F1-score = 0.91

Through meticulous examination of various research papers, we have observed that researchers frequently utilize models such as AlexNet, VGG, ResNet, SqueezeMNet, among others, to achieve remarkable accuracy and F1-scores, ranging from 76.09% to 99.3%. Our analysis encompassed datasets spanning ISIC 2016, 2017, 2018, 2019, and 2020. However, it is imperative to highlight that our detailed review revealed a concerning trend associated with preprocessing techniques, particularly in data augmentation. We identified a recurrent issue of random data creation and duplication resulting from these techniques. This phenomenon has significantly contributed to mispredictions, overfitting, biases, and a lack of generalization in the outcomes. Such challenges underscore the necessity for a more careful consideration of preprocessing methods to ensure the integrity and reliability of the data and subsequent analysis in the field of skin cancer diagnosis.

### 3.5 CNNs for the SCC and SCS Using ISIC Dataset

CNNs play a crucial role in advancing the classification and segmentation of skin lesions, leveraging datasets like ISIC for improved diagnostic accuracy. CNNs directly learn from data, excelling in image recognition and analysis tasks related to skin cancer detection [101]. Recognized as one of the most proficient machine learning algorithms, CNNs demonstrate remarkable performance in various image processing tasks and computer vision applications, including skin lesion localization, segmentation, classification, and detection [102]. Typically comprising tens or hundreds of layers, each responsible for recognizing distinct aspects of skin lesion images, CNNs operate by applying convolutional filters during training. These filters start by detecting fundamental features such as color variations, edges, and textures, progressively becoming more sophisticated, and ultimately identifying specific lesion characteristics [103]. Hidden layers between the CNN's input and output layers conduct operations that modify the data to learn features specific to the skin lesion dataset. The most commonly used layers include Convolution, activation (or ReLU), and pooling [104].

The Convolution layer is the fundamental building block, handling most of the computational workload. Through convolution, filters are applied to input skin lesion images, activating different lesion aspects. Mathematically, convolution can be expressed as:

$$S(i, j) = (I * K)(i, j) = \sum_m \sum_n I(m, n)K(i - m, j - n) \quad (1)$$

where  $S(i, j)$  represents the output of the convolution operation at position  $(i, j)$  in the resulting image or feature map. And  $(I * K)(i, j)$  This is the convolution operation between the input image  $I$  and the convolutional kernel  $K$  at the position  $(i, j)$  [105].  $\sum_m \sum_n$  are summation symbols that indicate a double summation over the indices  $m$  and  $n$ . The convolution operation involves summing up the elementwise product of corresponding elements of the input image and the flipped (or rotated) convolutional kernel. At the end,  $I(m, n)$  represents the pixel value of the input image at position  $(m, n)$  [106].  $K(i - m, j - n)$  represents the corresponding weight of the convolutional kernel at the relative position  $(i - m, j - n)$ . The kernel is typically smaller than the input image, and this term defines how the kernel is applied to different positions of the input [107].

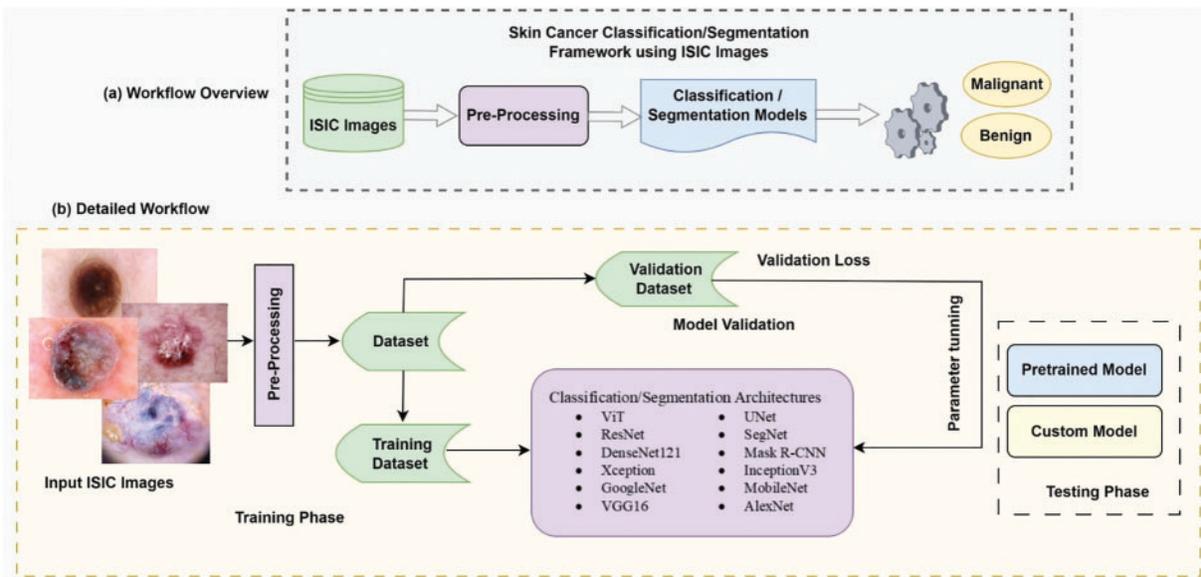
Activation functions, such as Rectified Linear Unit (ReLU), expedite training by introducing non-linearity and ensuring that only activated characteristics proceed to the subsequent layer. Mathematically, ReLU is defined as:

$$f(x) = \max(0, x) \quad (2)$$

where pooling is another essential layer that reduces the network's parameter count by performing nonlinear downsampling on the output [108]. Max pooling, for instance, can be expressed as:

$$P(i,j) = \max_{m,n} I(m+i, n+j) \quad (3)$$

These operations, including convolution, activation, and pooling, are repeated across multiple layers, where each layer learns to recognize diverse features of skin lesions. The final classification output is obtained from the top layer's classification layer in the CNN architecture. Fig. 12 demonstrates the overall methodology of ISIC image classification and segmentation in detail.



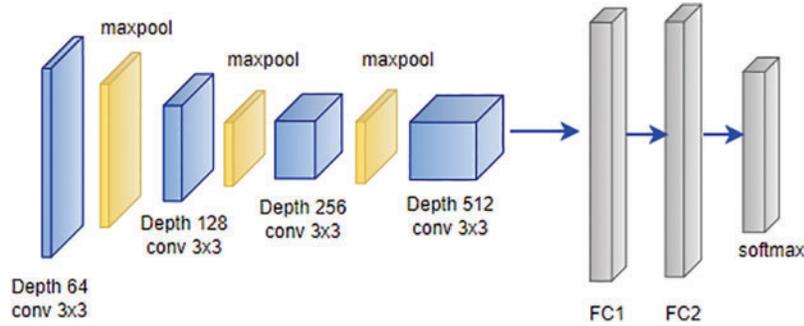
**Figure 12:** Overall methodology of ISIC images classification and segmentation

### 3.6 State-of-the-Art CNN Architectures for SCC and SCS Using ISIC Dataset

This section delves into the forefront of CNN architectures, demonstrating their mathematical and computational prowess in image classification and segmentation for skin cancer detection. These algorithms are utilized to enhance computational involvement for better results, specifically tailored to the ISIC dataset. Researchers have extensively explored these architectures to improve diagnostic accuracy. Key architectures employed in ISIC dataset studies include:

#### 3.6.1 VGG Architecture

VGG is a convolutional neural network architecture developed by Karen Simonyan and Andrew Zisserman at Oxford University's Visual Geometry Group [109]. The VGG-16 model, detailed in [110], attained an impressive 92.7% top-5 test accuracy on the ImageNet dataset, which encompasses 14 million images across 1000 classes. Simonyan and Zisserman enhanced performance by substituting large-size kernel filters with multiple  $3 \times 3$  kernel-sized filters, surpassing the capabilities of AlexNet [110]. VGG offers various configurations based on the number of convolution layers, with VGG-16 and VGG-19 being the most prevalent. The architecture of VGG-16, illustrated in Fig. 13, consists of thirteen convolution layers, a max-pooling layer, three fully connected layers, and an output layer [111].



**Figure 13:** Architecture of VGG

This model's architecture has demonstrated its efficacy in diverse image classification tasks, making it a valuable asset for researchers in the field [112]. The versatility of the VGG architecture extends to its application in skin cancer detection using the ISIC dataset. Researchers have harnessed the power of VGG-16 and VGG-19 configurations to address the intricacies of skin lesion classification and segmentation [113]. The rich diversity of skin images within the ISIC dataset aligns seamlessly with VGG's ability to capture complex features. By adapting the pre-trained VGG models on ImageNet to the specific characteristics of skin cancer images from the ISIC dataset, studies have achieved remarkable results [114]. Fine-tuning VGG architectures with transfer learning techniques allows the models to grasp subtle patterns indicative of various skin conditions. The robust performance demonstrated by VGG in broader image classification tasks translates effectively to the nuanced domain of skin cancer detection within the ISIC dataset [115].

$$y = f(W_x + b) \quad (4)$$

Eq. (4), inherent to VGG's convolutional layers, encapsulates the mathematical foundation of its adaptability and effectiveness in processing skin images from the ISIC dataset. This synergy between VGG architecture and the ISIC dataset underscores the significance of leveraging state-of-the-art models for advancing the accuracy and reliability of skin cancer detection systems.

### 3.6.2 AlexNet

AlexNet, introduced by Hosny et al. [116], is a pioneering CNN architecture renowned for revolutionizing image classification tasks. Comprising five convolutional layers and three fully connected layers, as depicted in Fig. 6, AlexNet played a pivotal role in winning the ImageNet LSVRC in 2012 [117]. With a total of 60 million parameters, AlexNet effectively addressed overfitting concerns through the innovative integration of dropout layers, enhancing the model's generalization capabilities:

$$P(\text{dropout}) = 0.5 \quad (5)$$

where  $P(\text{dropout})$  represents the probability of dropout, this equation signifies that during training, each neuron has a 50% chance of being dropped out, preventing reliance on specific neurons and promoting better generalization [118]. Beyond its success on ImageNet, AlexNet's architecture has become a foundational blueprint for subsequent deep learning models, contributing significantly to the advancement of computer vision applications [119]. Trained on ImageNet LSVRC-2010, AlexNet demonstrated remarkable performance with top-1 and top-5 error rates of 37.5% and 17.0%, respectively, solidifying its position as a landmark in the evolution of deep learning architectures. The softmax activation function used in the final layer is defined as:

$$P(class_i) = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}} \quad (6)$$

where  $P(class_i)$  is the probability of the input belonging to class  $i$ ,  $z_i$  is the raw output for class  $i$ , and  $K$  is the total number of classes [120]. This equation reflects the normalization of raw outputs into class probabilities, facilitating effective multiclass classification. Fig. 14 demonstrates the architecture of AlexNet in detail.

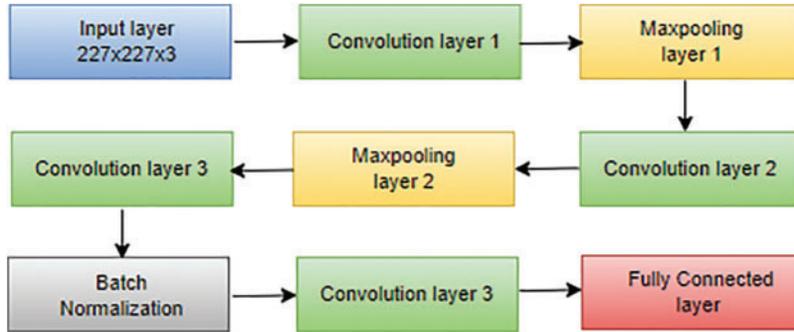


Figure 14: Architecture of AlexNet

### 3.6.3 ResNet

AlexNet secured victory in the ImageNet 2012 competition, featuring an original eight-layer architecture. In the landscape of deep learning, the common strategy of adding more layers aims to boost performance and reduce error rates [121]. However, this approach introduces challenges like vanishing gradients, where the gradient approaches zero, and exploding gradients, where the gradient becomes excessively large. Addressing these challenges, He et al. [122] introduced skip connections, an innovative concept to alleviate problems associated with exploding and vanishing gradients. Skip connections involve bypassing certain levels between layers and directly linking layer activations to subsequent layers, forming what is known as residual blocks [123]. The ResNet architecture stands as a powerful tool for researchers aiming to construct and train deep neural networks effectively. The equations for ResNet skip connections can be expressed as follows, where  $x$  represents the input to a particular layer,  $F$  denotes the operations within a residual block, and  $y$  is the output [124]:

$$y = F(x) + x \quad (7)$$

This novel approach serves as the foundation of the ResNet architecture, depicted in Fig. 15. ResNet's skip connections enable the bypassing of problematic layers during training, effectively mitigating issues related to exploding and vanishing gradients [125]. This architectural innovation has proven instrumental in facilitating the training of deep neural networks, providing a practical solution to challenges encountered with increasing network depth [126].

### 3.6.4 MobileNet

Howard et al. [127] introduced a lightweight network called MobileNet specifically designed for mobile applications. In MobileNet, the traditional  $3 \times 3$  convolution operation found in standard CNNs is replaced with a combination of a  $3 \times 3$  depthwise convolution and a  $1 \times 1$  pointwise convolution operation. This strategic use of depthwise separable convolution, as opposed to the standard convolution operation, proves effective in reducing the overall number of training parameters

[128]. The distinction between the standard convolution operation and the depthwise separable convolution employed in MobileNet is illustrated in Fig. 16.

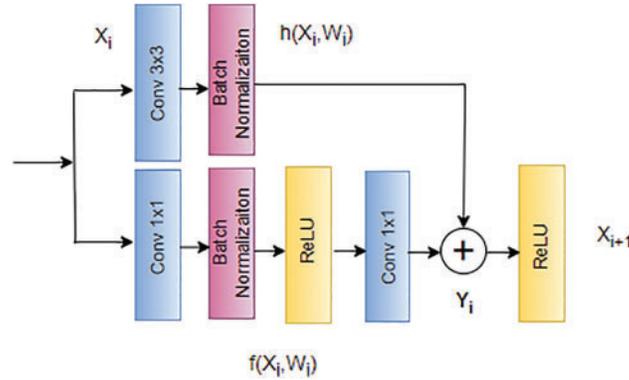


Figure 15: Architecture of ResNet

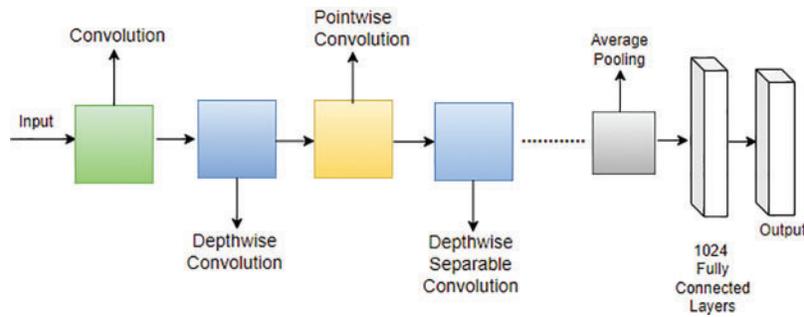


Figure 16: Architecture of MobileNet

This modification in the convolutional operation contributes to the efficiency of MobileNet, making it well-suited for deployment on mobile devices by significantly reducing computational demands and model size [129]. MobileNet represents a noteworthy advancement in tailoring neural network architectures for optimal performance on resource-constrained platforms [130]. Moreover, MobileNet’s architecture is characterized by the following equations for depthwise convolution and pointwise convolution:

**Depthwise convolution:**

$$y = \text{depthwise}_{\text{conv}}(x, w) = \sum_k x * w_k \tag{8}$$

**Pointwise convolution:**

$$z = \text{pointwise}_{\text{conv}}(y, b) = \sum_k y_k + b_k \tag{9}$$

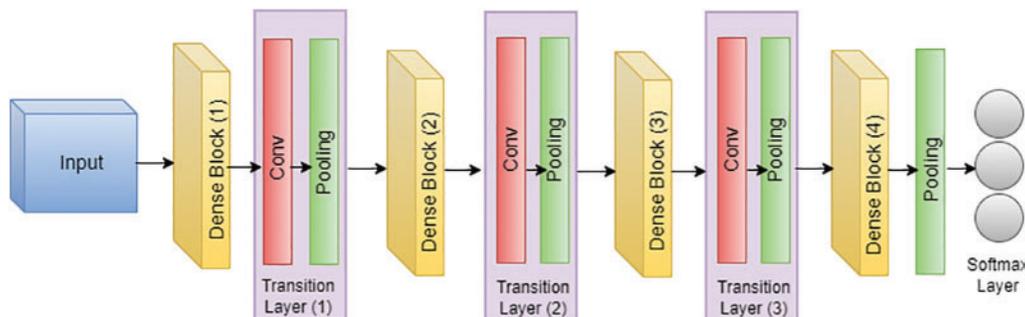
In these equations,  $x$  represents the input,  $w$  denotes the depthwise convolutional kernel,  $y$  is the intermediate output after depthwise convolution,  $z$  is the final output after pointwise convolution, and  $b$  represents the bias term [131]. The depthwise convolution is followed by batch normalization and ReLU activation, contributing to the overall efficiency of MobileNet [132].

### 3.6.5 DensNet

In the groundbreaking work by Huang et al., the DenseNet architecture, or densely connected convolutional network, was introduced, and its application to skin cancer classification and segmentation, specifically on the ISIC dataset, has demonstrated notable success [133,134]. Illustrated in Fig. 17, DenseNet's unique connectivity pattern, where each layer is directly connected to every other layer, proves advantageous in capturing intricate features inherent in skin lesion images. For skin cancer classification, DenseNet leverages the comprehensive information flow between layers, utilizing feature maps from all preceding layers as inputs for each subsequent layer [135,99]. This connectivity scheme mitigates the vanishing gradient problem and enhances the model's ability to discern nuanced patterns indicative of different skin conditions within the ISIC dataset [136,137]. In the domain of segmentation, DenseNet's connectivity pattern contributes to robust feature propagation throughout the network, aiding in the precise delineation of lesion boundaries. The efficiency gains from reduced parameters make DenseNet well-suited for handling the complexities of skin cancer images in the ISIC dataset [138,139]. The connectivity equation for DenseNet, tailored to the ISIC dataset, is expressed as follows, where  $x_i$  denotes the feature map of the  $i^{\text{th}}$  layer and  $[x_0, x_1, x_2 \dots x_{i-1}]$  represents the concatenation of feature maps from all preceding layers:

$$x_i = H_i([x_0, x_1, x_2 \dots x_{i-1}]) \quad (10)$$

This adaptation underscores the efficacy of DenseNet in processing ISIC dataset images, emphasizing its role in advancing both skin cancer classification and segmentation tasks [140].



**Figure 17:** Architecture of DensNet

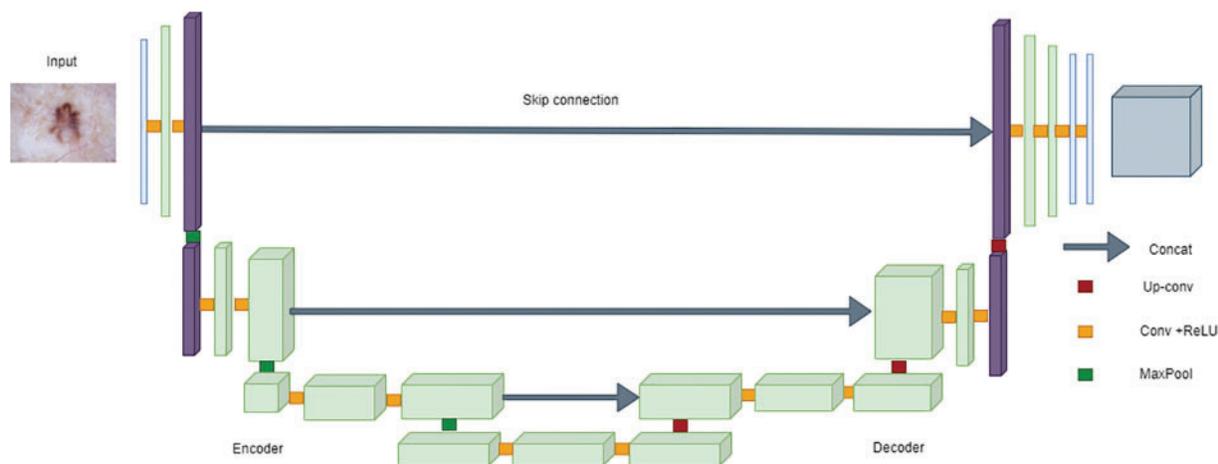
### 3.6.6 U-Net

U-Net's popularity in medical image segmentation, particularly for skin cancer segmentation on the ISIC dataset, can be attributed to its robust architecture [141,142]. The encoder-decoder structure, complemented by skip connections, facilitates the accurate localization of skin lesions. The model's effectiveness lies in its ability to maintain a seamless flow of information between the encoder and decoder, enabling precise delineation of lesions in the challenging scenarios posed by the ISIC dataset [143,144]. The incorporation of skip connections proves pivotal in retaining fine-grained details during upsampling, a crucial factor contributing to U-Net's remarkable success in skin cancer segmentation [145,146]. The following equation can succinctly represent the architecture of U-Net:

$$\text{Output} = \sigma (\text{Decoder} (\text{Encoder}(\text{Input}) + \text{Skip Connections})) \quad (11)$$

where  $\sigma$  denotes the sigmoid activation function, and the skip connections play a crucial role in preserving detailed information during the segmentation process. Additionally, U-Net's adaptability

and ease of implementation, as expressed by this equation, make it a preferred choice for researchers and practitioners in the field of medical image analysis [147,148]. Fig. 18 illustrates UNet architecture in detail.



**Figure 18:** Architecture of UNet

### 3.6.7 SegNet

SegNet is a convolutional neural network architecture tailored for pixel-wise image segmentation tasks, making it suitable for applications like skin lesion segmentation in the ISIC dataset [149,150]. Its design includes an encoder-decoder structure with symmetrically paired encoder and decoder layers. SegNet utilizes max-pooling indices from the encoder during the upsampling process, aiding in preserving spatial information crucial for accurate segmentation [151,152]. The model's architecture enhances the localization of intricate features within skin lesions, contributing to its effectiveness in the challenging context of the ISIC dataset. SegNet's performance is often attributed to its focus on retaining fine-grained details, demonstrating its utility in medical image segmentation, particularly for dermatological applications [153,154].

$$\hat{Y} = \text{Decoder}(\text{Encoder}(X)) \quad (12)$$

This equation represents the forward pass of SegNet, where  $X$  is the input image, Encoder that performs the encoding operation, and Decoder performs the decoding operation to generate the segmented output  $\hat{Y}$  [155].

In the realm of SCC and SCS using the ISIC dataset, various models, including AlexNet, VGG, ResNet, and SqueezeMNet, have been extensively employed by researchers, yielding commendable accuracy and F1-scores ranging from 76.09% to 99.3%. Notably, in the domain of SCS, particularly utilizing the ISIC dataset across multiple iterations, significant advancements have been made with the adoption of specialized models such as InSiNet and U-Net. In recent investigations spanning ISIC 2018, ISIC 2019, and ISIC 2020 datasets, these models have demonstrated notable efficacy, achieving commendable accuracy rates. Specifically, across the respective datasets, segmentation accuracies of 94.59%, 91.89%, and 90.54% have been attained. These results underscore the continual refinement and adaptation of deep learning architectures to address the challenges inherent in SCS. Such accuracies not only reflect the robustness of the models but also signify their potential utility

in clinical settings for aiding dermatologists in accurate diagnosis and treatment planning. Each model presents distinct advantages and disadvantages in the context of ISIC data utilization. AlexNet, renowned for its pioneering role in deep learning, offers a relatively straightforward architecture and efficient training, making it suitable for initial experimentation. However, its shallower depth may limit its ability to capture intricate features in complex skin lesion images. VGG, characterized by its deeper architecture, excels in feature extraction but suffers from increased computational complexity and memory requirements, potentially limiting its scalability. ResNet, with its residual connections, mitigates the vanishing gradient problem and facilitates the training of deeper networks, thereby enhancing feature representation. Nonetheless, its extensive depth may lead to overfitting, particularly with smaller datasets. SqueezeMNet, notable for its lightweight architecture, enables efficient inference on resource-constrained devices, but may sacrifice some accuracy compared to larger models. InSiNet incorporates attention mechanisms, allowing for dynamic focus on salient regions within the ISIC input image. This adaptability can enhance segmentation accuracy, particularly in cases with complex or heterogeneous cancer. U-Net, renowned for its ability to effectively capture fine-grained details in ISIC image segmentation tasks, features a symmetric architecture with contracting and expansive pathways. This design facilitates precise delineation of lesion boundaries, leading to accurate segmentation results. Despite their strengths, all these models are susceptible to the aforementioned issue of data duplication resulting from preprocessing techniques. This recurring challenge has posed significant obstacles, including mispredictions, overfitting, biases, and a lack of generalization, underscoring the critical need for meticulous consideration of preprocessing methods to uphold the integrity and reliability of both the data and subsequent analyses in skin cancer diagnosis.

#### 4 Challenges

After conducting an exhaustive review of existing literature, it has been discerned that the incorporation of preprocessing techniques to expand ISIC datasets presents a myriad of challenges, thereby exerting a discernible impact on the reliability and accuracy of the outcomes:

1. **Random duplication in images:** Preprocessing methodologies often engender the random duplication of images within the ISIC dataset. This inadvertent replication can lead to the recurrence of identical or highly similar images multiple times, thus precipitating erroneous predictions during both the training and evaluation phases of model development. Additionally, such random duplication exacerbates the problem of imbalanced data, where certain classes may be overrepresented while others are underrepresented, further complicating model training and evaluation.
2. **Overfitting due to replicated data:** The replication of data facilitated by preprocessing techniques may inadvertently induce overfitting of the model on the ISIC dataset. Overfitting, a phenomenon characterized by the model's tendency to memorize the intricacies of the training data rather than generalize from it, can yield ostensibly superior performance metrics on the training dataset. However, such models often exhibit suboptimal generalization capabilities on unseen data, thereby impugning the reliability and robustness of the resultant outcomes.
3. **Reduced diversity and generalizability:** The process of replicating data through preprocessing interventions has the potential to attenuate the diversity inherent within the ISIC dataset. This reduction in diversity, precipitated by the introduction of identical or highly similar images, can impede the model's capacity to generalize effectively to novel, unseen data instances. Consequently, this limitation culminates in a concomitant reduction in overall performance and reliability.

4. **Inefficient resource utilization:** The augmentation of ISIC datasets via preprocessing methodologies significantly amplifies the dataset's size, thereby engendering inefficiencies in terms of memory and computational resource utilization during model training. The resultant elongated training times and augmented computational costs detrimentally affect the scalability and practical applicability of the model.
5. **Introduction of biases:** Preprocessing techniques may inadvertently introduce biases into the ISIC dataset, particularly in instances where the augmentation strategies are inadequately designed or implemented. The inadvertent introduction of biases can skew the model's learning trajectory, precipitating biased predictions and ultimately compromising the fairness and reliability of the resultant outcomes.

Addressing these multifarious challenges necessitates a comprehensive understanding of the potential pitfalls associated with preprocessing techniques, as well as the judicious implementation of rigorous validation and quality control measures to safeguard the integrity and reliability of both the ISIC dataset and the ensuing model. Moreover, strategies to mitigate imbalanced data problems, such as class weighting or data resampling techniques, are imperative to ensure equitable representation of all classes and enhance the model's performance and generalizability.

## 5 Future Directions

In future directions, addressing the challenge of random duplication in ISIC datasets resulting from the use of distinct augmentation techniques is paramount. Such duplications can lead to misleading outcomes and adversely affect real-time analysis, potentially increasing the incidence of true negative predictions and thereby promoting erroneous conclusions. To tackle this issue effectively, the integration of ViTs with their encoder-decoder architectures and attention mechanisms emerges as a promising approach. ViTs are renowned for their adeptness in feature extraction, while the ViT encoder-decoder framework offers the additional capability of generating diverse and realistic data samples. This integration presents a holistic solution for mitigating the impact of duplicated data on analysis outcomes. Moreover, by combining these techniques with ResNet, a well-established algorithm for feature extraction, there is an opportunity to bolster the detection of false positives in diagnosis as SCC and SCS. In the envisioned architecture, the encoder-decoder aspect of the ViT framework plays a crucial role. The encoder processes input images and extracts relevant features, while the decoder generates output predictions based on these features, thereby enabling both feature extraction and generation of diverse data samples. By amalgamating these methodologies, a more robust framework for ISIC image analysis can be established, leading to enhanced diagnostic accuracy and reliability in clinical settings.

## 6 Conclusion

In conclusion, this paper has highlighted the multifaceted challenges encountered in utilizing preprocessing techniques to expand ISIC datasets for skin cancer classification and segmentation. These challenges include random duplication in images, overfitting due to replicated data, reduced diversity and generalizability, inefficient resource utilization, and the introduction of biases. Collectively, these factors impede the reliability and accuracy of outcomes derived from machine learning models trained on such datasets. Addressing these challenges requires a comprehensive understanding of the pitfalls associated with preprocessing techniques, as well as the implementation of rigorous validation and quality control measures. Strategies to mitigate imbalanced data problems, such as class

weighting or data resampling techniques, are essential to ensure equitable representation of all classes and enhance model performance and generalizability. Looking ahead, future directions outlined in this paper propose innovative approaches to overcome the challenge of random duplication in ISIC datasets. The integration of ViTs with its robust architecture offers an opportunity to enhance the detection of false positives in diagnosis, contributing to improved diagnostic accuracy and reliability in image datasets. This systematic review paper underscores the importance of addressing the challenges associated with preprocessing techniques in ISIC dataset utilization for skin cancer analysis. By delineating future directions and proposing innovative solutions, this paper contributes to advancing the field of skin cancer diagnostics, ultimately benefiting patient care and global healthcare initiatives. This study elucidates the pivotal role of mathematical and computational modeling in enhancing skin cancer detection methodologies, paving the way for more accurate and reliable diagnostic tools in dermatological image analysis research.

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**Availability of Data and Materials:** The data will be made available by the corresponding author upon reasonable request.

**Conflicts of Interest:** The authors declare that they have no conflicts of interest to report regarding the present study.

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