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Review Article

Unveiling Skin Cancer: A Review of Deep Learning Techniques for Detection

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Abstract: Early identification is essential for successful treatment and better patient outcomes since skin cancer is caused by damage to DNA in skin cells, which can result in genetic abnormalities and the possibility of metastasis. The present systematic review scrutinizes the efficacy and obstacles of early detection techniques, which differentiate between benign and malignant lesions by examining lesion attributes such as symmetry, color, size, and form. Image quality and expert interpretation are two elements that have an impact on the accuracy of existing techniques. This review assesses the accuracy, precision, and other validation measures of a variety of computer vision approaches and algorithms, including machine learning and deep learning. The results show how these sophisticated algorithms have significantly improved cancer identification, laying the groundwork for further studies and highlighting prospects to improve deep learning-based skin cancer detection.

Keywords: Convolutional Neural Network (CNN), Deep Neural Network (DNN), Transfer Learning, Vision Transformer (VIT)

Introduction

Cancer is a complex disease defined by the excessive growth or division of abnormal cells in the body. It is not limited to humans; it also impacts animals and other forms of life. The cells in question originate from gene changes, which cause a single cell or a group of only a few cells to grow excessively and divide uncontrollably, resulting in a tumor. Additionally, cancer cells possess the ability to break away from the original mass of cells and navigate through the bloodstream and lymphatic systems which settles on another organ causing the cycle of uncontrolled growth. This phenomenon of cancer cells spreading from one area to grow in another part of the body is referred to as metastatic spread or metastasis. There are over 200+ different types of cancer, and 9 in 10 individuals in the UK are expected to face a cancer diagnosis during their lifetime. Most cancers may be due to the gene changes that accumulate over a person's lifespan, some are linked to inherited faulty genes, although this occurrence is rare (Imran *et al.*, 2022). While many cancers can be successfully treated and cured, there is the possibility of cancer recurrence in some cases. Additionally, there are instances where certain cancers cannot be completely cured, but treatments are often effective in controlling the disease for several years.

When cancer starts in the skin, it is known as skin cancer. Skin cancer occurs when factors such as exposure ultraviolet light lead to alterations in the growth of skin cells. Recognizable symptoms include when new bunches or bits of skin show up, or when the size, shape, or shade of existing skin development changes. Early detection is important because most instances of skin cancer can be controlled when they are detected early. Cancers are classified on the TNM system as one of five stages: Primary Tumor, Nodes, and Metastasis. Stage 0 - no cancer, abnormal cells, or starting of cancer. Stage I - T1-T2, N, M0 is small cancer at a particular area, this Stage is also known as small cancer or early-stage cancer, stage II -T2- T4, N0, M0, and Stage III - T1-T4, N1-N3, M0, large cancer and abnormal growth of cells and through nearby lymph nodes or tissues. Stage IV - T1-T4, N1-N3, M1 advanced or metastatic cancer, where the cancer spreads to other bodies. This staging system helps develop treatment plans and another diagnosis in the process of cancer treatment. Studies show that 7,099 Americans die from skin cancer, accounting for 97,160 new cases per year in the United States. Based on increased sun exposure, basal cell carcinoma is one of the three primary forms of skin cancer. Melanoma and Squamous Cell Carcinoma. The worst resistant skin cancer that swiftly spreads to other body parts is melanoma. Melanocytes, which are skin cells that create the melanin pigment responsible for skin color, are the source of melanoma.

Between 2016 and 2020, there were around 21 cases of melanoma per 100,000 persons in the US. Melanoma claimed the lives of 2.1 persons for every 100,000 instances throughout this time; by 2020, 1,413,976 cases of the illness had been reported. The five-year survival rate for skin melanoma is 93.5%, which is still quite high and indicates that treatment may be helpful. Forecasts indicate that in 2023, there will be an estimated 186,680 new cases of melanoma in the US. Of those, 89,070 are projected to be non-invasive (in situ) and limited to the epidermis, while 97,610 will be invasive and reach the dermis. Timely discovery is crucial, as evidenced by the considerable improvement in survival rate to 99.6% after early diagnosis. Only 77.6% of skin melanomas, on the other hand, are identified while the cancer is confined and has not spread to other bodily regions. Early detection of skin melanoma is essential to lowering the number of fatalities linked to this illness. Analyzing and surveying skin cancer is essential to resolving the public health issues related to this common ailment. Understanding the dynamics of skin cancer requires tracking and researching the disease's incidence, prevalence, and demographic trends. Researchers can uncover risk factors, regional trends, and new patterns through thorough surveys, which can provide important information for targeted treatments and preventative actions. Early detection is crucial for the successful treatment of skin cancer, and routine analysis facilitates the identification of high-risk individuals and areas. Additionally, this research aids in the creation of public health campaigns, educational efforts, and awareness campaigns that support sun protection behaviors, frequent skin exams, and a proactive attitude toward skin health. In essence, the ongoing analysis and survey of skin cancer are integral components of a broader strategy to reduce the impact of the disease, improve outcomes, and enhance overall community well-being.

Research Methodology

The purpose of the literature review is to identify and classify the most effective Deep Neural Network-based techniques for skin cancer screening. Such reviews provide an integrative insight into the current available knowledge through the collection and analysis of existing studies based on pre-defined evaluation criteria. Systematic literature reviews form the core of research domains to derive the existing states of affairs along with the prevalent gaps, which further guide future investigation and development. A systematic literature review offers more structure, coherence, rationality, and support in answering the underlying research question when data are collected from primary sources and organized for analysis. This current review focuses on research papers relevant to Skin Cancer detection employing DNN techniques.

Research Framework

Establishing the review framework was the first stage in this process. A thorough plan consisting of three unique phases planning, data collection and validation, and findings production and conclusion, was followed to execute the systematic literature review.

Search Strategy

Arranging a methodical and organized search is essential to obtaining relevant content from the target domain. This stage involved a comprehensive search to glean pertinent and useful information from the massive volume of data, to collect content from all sources that pertain to the target topic, such as case studies, research papers, and reference lists of publications that are closely relevant. Furthermore, a thorough analysis was conducted of websites that provided details on skin cancer, its causes and risks, and neural network methods for detecting it. We used the specified parameters to guide our search to retrieve the needed and pertinent facts.

Finding phrases and keywords, choosing words that are associated with these keywords, and creating search strings using logical operators are all part of the process. After selecting keywords associated with deep learning methods for detecting skin cancer, synonyms were added to the search. To hone the search, logical operators 'AND' and 'OR' were utilized in between terms.

Search Resources

We started our investigation by using reliable resources like IEEE Xplore, Springer, and Google Scholar to learn more about neural network methods for skin cancer diagnosis. In this stage, we had to locate and gather fundamental research that was pertinent to our subject. After that, we conducted additional analysis on the chosen research articles using pre-established rating standards.

Selection Criteria

Specific inclusion criteria used for the first phase of research paper selection were the language in which the paper was written, its publication year, and relevance to the desired domain. For this paper, only papers in the English language will be considered. This review focuses on research from 2018 to 2024, ensuring that selected papers correspond very much with search terms as detailed in our search strategy.

Skin Cancer

The majority of cases of skin cancer are caused by prolonged exposure to ultraviolet (UV) radiation; tanning beds and sun exposure are two significant contributing factors. Excessive exposure causes unrestrained growth and division of skin cells, which can be regulated by genetics and skin type because DNA damage cannot be repaired by the body. Fair skin, moles, precancerous skin lesions, a family history of skin cancer, excessive sun exposure, living in warm, sunny climates, weakened immune systems, radiation exposure, and exposure to certain chemicals like arsenic are additional risk factors. The immune system can be weakened by comparable circumstances and exposure to pollutants. Skin cancer manifests in four main types: Basal cell carcinoma, which typically arises from radiation therapy or sun exposure and tends to grow slowly without spreading widely, often affecting the head and neck (Imran *et al.*, 2022). Squamous cell carcinoma, caused by factors like sun exposure, damaged skin, chemicals, or exposure to X-rays, constitutes about 20% of skin cancer cases and commonly occurs in the lips and mouth, with a small proportion spreading to other body parts (Naeem *et al.*, 2024). These two types are grouped under keratinocyte carcinoma (Thanga Purni & Vedhapriyavadhana, 2024), also known as non-melanoma skin cancer. Merkel cell cancer originates from hormone-producing cells and hair follicles, presenting as a highly aggressive and fast-growing cancer primarily found in the neck and head region, also termed neuroendocrine carcinoma.

Melanoma, the most serious kind of skin cancer, penetrates the skin deeply, contaminates blood vessels, and destroys skin to spread to lymph nodes and other parts of the body. Melanocytes, which are found in the deepest layer of the epidermis, are responsible for producing the pigment or color of the skin (Alabdulkreem *et al.*, 2024). Melanoma can occur anywhere in the body. Using sophisticated procedures and dermatological photos, melanoma risk assessment is one of the strategies used to identify skin cancer. Dermatologists' eye exams are the primary means of diagnosis; dermoscopy can increase accuracy to 89% (Alabdulkreem *et al.*, 2024). Still, it can be difficult to diagnose certain tumors correctly, particularly early melanomas with no distinguishing symptoms. Computer-aided detection methods have been developed to address this, involving image processing, feature extraction, segmentation, feature selection, and classification. Machine learning techniques hold promise for enhancing skin cancer diagnosis accuracy, particularly deep learning methods (Jaisakthi *et al.*, 2023), which excel in extracting detailed features from lesion images. Recent studies employing diverse deep learning algorithms have shown promising results, paving the way for even more precise and efficient diagnostic tools in skin cancer detection (Jaisakthi *et al.*, 2023).

Skin Cancer Types

- Melanoma: The most dangerous kind of skin cancer is melanoma (Banerjee *et al.*, 2020; Fraiwan & Faouri, 2022), yet it is less common than squamous and basal cell carcinomas. Originating from melanocytes, it can swiftly metastasize to other organs if not detected early. Melanoma can develop anywhere on the skin, including the eye (Fraiwan & Faouri, 2022). In men, it commonly appears on the trunk, head, or neck, while in women, it's often found on the arms and legs.
- Dysplastic Nevi: A type of mole also termed as atypical mole that looks different from normal mole. This mole looks bigger, different color, and surface, a slightly scaly surface. Dysplastic nevus occurs anywhere on the body mostly seen in areas exposed to sun (Banerjee *et al.*, 2020).
- Basal Cell Carcinoma (BCC): This cancer develops mainly in people who undergo radiation therapy or sun exposure, grows slowly, and rarely spreads. Mostly develops on the head and neck. Basal cells are round-shaped cells in which about 80% of skin cancer develops (Qasim Gilani *et al.*, 2023). If it's not treated, this can continue to grow deeper under the skin and cause destruction of surrounding tissues. It was almost cured when it was found early.
- Squamous Cell Carcinoma (SCC): Develops due to sun exposure, damaged skin, chemicals, or exposure to x-rays. 20% of skin cancer develops from squamous cells (Tyagi *et al.*, 2022; Qasim Gilani *et al.*, 2023). These cells are commonly found in the lips and mouth. About 2% of cancer spreads to other parts of the body. These two types of cancer are also grouped together and known as keratinocyte carcinoma. That is, Keratinocyte carcinoma is the medical term used to denote non-melanoma skin cancer.
- Actinic Keratoses (Aks): Years of sun exposure can lead to the development of a rough, scaly patch on the skin. Mostly found on lips, face, ears scalp, and neck. It is also known as solar Keratosis. Grows slowly and first appears in people above 40. This can be reduced by protecting themselves from Ultraviolet rays (Hamida *et al.*, 2024; Thurnhofer-Hemsi & Domínguez, 2021).

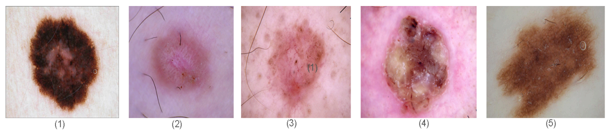

Fig. 1: (1) Melanoma,(2) Dysplastic Nevi, (3) Basal Cell Carcinoma (BCC), (4) Squamous Cell Carcinoma (SCC), (5) Actinic Keratoses (Aks)

As shown in Figure 1, various types of skin lesions can be observed, including Melanoma (1) Melanoma,(2), Dysplastic Nevi (3), Basal Cell Carcinoma (BCC) (4), Squamous Cell Carcinoma (SCC) (5), and Actinic Keratoses (Aks).

Exploring the Efficacy of Convolutional Neural Networks (CNNs) in Image Classification

Convolutional Neural Networks (CNNs) stand as formidable tools in the realm of machine learning, particularly adept at deciphering grid-like structured data such as images (Tyagi *et al.*, 2022). Their prowess in tasks like image recognition, localization, segmentation, and classification is well-documented (Tyagi *et al.*, 2022). Typically composed of numerous layers, CNNs

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are structured to discern diverse facets of an image. As data flows through the network, each layer refines its understanding, progressing from simple features like brightness and edges to more intricate object-specific attributes (Tyagi *et al.*, 2022). Hidden layers within the CNN perform operations to extract data-specific features, with convolution, activation (ReLU), and pooling layers being the most prevalent (Kausar *et al.*, 2021). Convolution, the cornerstone operation, applies filters to input images, uncovering various aspects crucial for classification. Activation functions, such as ReLU, enhance training efficiency by selectively preserving activated characteristics. Pooling layers further streamline the process by downsampling, reducing the network's parameter count. Through iterative refinement across multiple layers, CNNs learn to discern increasingly complex features, culminating in the final classification provided by the network's topmost classification layer (Kausar *et al.*, 2021).

AlexNet

Alex Krizhevsky, Ililya Sutskever, and Geoffrey Hinton created the revolutionary convolutional neural network (CNN) known as AlexNet. It enhanced training efficiency by utilizing GPU acceleration. The architecture of AlexNet is comprised of five convolutional layers, three max-pooling layers, two normalization layers, two fully connected layers, and one SoftMax layer, as seen in Figure 2. AlexNet had an astounding 60 million parameters, but to prevent overfitting, its architecture included dropout layers. The model achieved remarkable top-1 and top-5 error rates of 37.5% and 17.0%, respectively, using the ImageNet LSVRC-2010 dataset (Naqvi *et al.*, 2023).

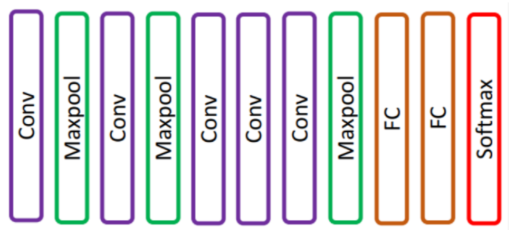

Fig. 2: AlexNet architecture, as described in Naqvi *et al.* (2023)

VGG

VGG 16 is a prominent convolutional neural network (CNN) architecture developed by the Visual Geometry Group (VGG) at the University of Oxford (Angelina & Ulfitria, 2024). The word "VGG" was coined by the research team behind its construction. Thirteen convolutional layers and three fully connected layers make up the network's total of sixteen layers, shown by the asterisk "16" (Bechelli & Delhommelle, 2022; Angelina & Ulfitria, 2024). As shown in Figure 3, the VGG 16 architecture stands out from other CNN designs due to its depth and simplicity. One noteworthy feature of VGG 16 is that, throughout the network, modest 3x3 convolutional filters are consistently used (Bechelli & Delhommelle, 2022).

ResNet

Renowned convolutional neural network (CNN) architecture VGG 16 was developed by the University of Oxford's Visual Geometry Group (VGG). The group that created it is the source of the "VGG" in its name. The network's total number of layers is represented by the "16"; it consists of three fully connected layers and thirteen convolutional layers (Bechelli & Delhommelle, 2022; Angelina & Ulfitria, 2024), VGG 16 architecture (Figure 3). In contrast to several other CNN architectures that employ intricate designs, VGG 16 maintains a deep level of simplicity. The network's ubiquitous application of tiny 3x3 convolutional filters is one of its distinguishing features.

Fig. 3: VGG-16 network presented in Naqvi *et al.* (2023)

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun introduced a groundbreaking deep residual learning network for image recognition. This innovative approach incorporates skip connections, a pivotal technique aimed at mitigating the challenges posed by vanishing and exploding gradients in deep neural networks (Jain *et al.*, 2021). This approach involves creating residual blocks within a ResNet architecture (Figure 4), where skip connections enable the network to bypass certain layers during training, mitigating issues related to gradient vanishing or exploding and contributing to the successful training of deep neural networks (Jain *et al.*, 2021).

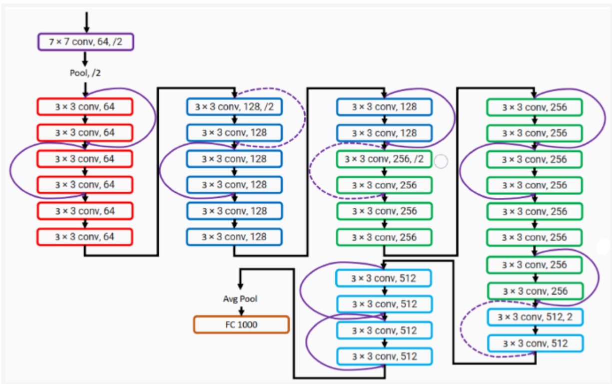

Fig. 4: ResNet architecture, as described in Naqvi *et al.* (2023)

DenseNet

DenseNet,is similar to ResNet, is a densely linked convolutional network designed to address accuracy

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issues arising from the deep neural network vanishing gradient problem (Kousis *et al.*, 2022). The reason for this problem is that information dissipates before it reaches the output layer because of the significant distance between the input and output layers (Thurnhofer-Hemsi & Domínguez, 2021).

In DenseNet, every layer uses its feature map as an input for every layer that comes after it, and all previous layers' feature maps are incorporated into each layer as well. The architecture of DenseNet is shown in Figure 5.

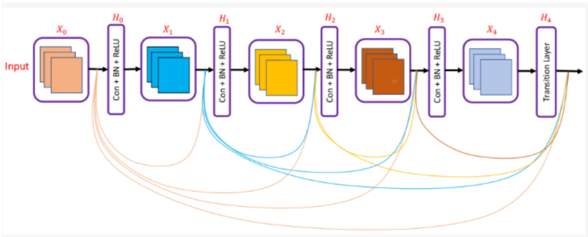

Fig. 5: Architecture of DenseNet Network presented in Naqvi *et al.* (2023)

MobileNet

A TensorFlow-based computer vision is a light and efficient convolutional neural network system for mobile applications. MobileNets, tailored for TensorFlow, are a family of computer vision models prioritizing efficiency for on-device or embedded applications by maximizing accuracy within constrained resources (Junayed *et al.*, 2021). The distinguishing traits of these models lie in their compact size, minimal latency, and low power requirements, making them versatile for a range of applications including classification, detection, embeddings, and segmentation (Junayed *et al.*, 2021). Remarkably, the number of trainable parameters is decreased by replacing the traditional 3×3 convolution with a depthwise separable convolution (which consists of a 3×3 depthwise convolution and a 1×1 pointwise convolution) (Junayed *et al.*, 2021). The MobileNet architecture is shown in Figure 6.

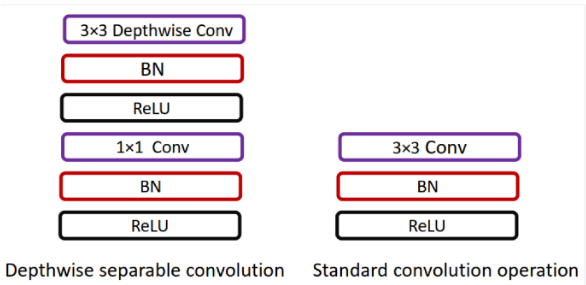

Fig. 6: Comparing Depthwise Separable Convolution with Standard Convolution Operation, as used in Naqvi *et al.* (2023)

Xception

Xception is an innovative convolutional neural network architecture introduced by François Chollet, the developer of Keras. The name "Xception" stands for "Extreme Inception," drawing inspiration from the Inception architecture (Jain *et al.*, 2021). Unlike traditional convolutional layers, Xception pushes the idea of factorizing convolutions to its limits. It achieves this by replacing standard convolutions with depthwise separable convolutions. Standard convolutions involve kernels sliding through the entire input volume, computing dot products with each part of the input. Depthwise separable convolutions split the convolution process into two independent phases: depthwise convolution and pointwise convolution. Every input channel receives a distinct application of a single filter during the depthwise convolution step. Next, a 1x1 convolution is executed on every channel in the pointwise convolution step. With a significant decrease in parameters and calculations due to this split, Xception becomes more efficient without sacrificing performance. The architecture of Xception is displayed in Figure 7.

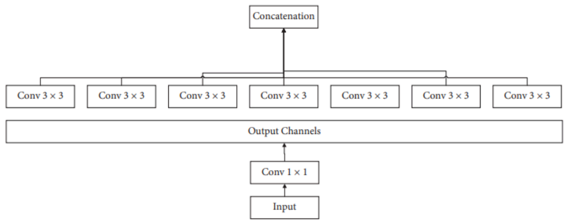

Fig. 7: Xception network presented in Lu & Firoozeh Abolhasani Zadeh (2022)

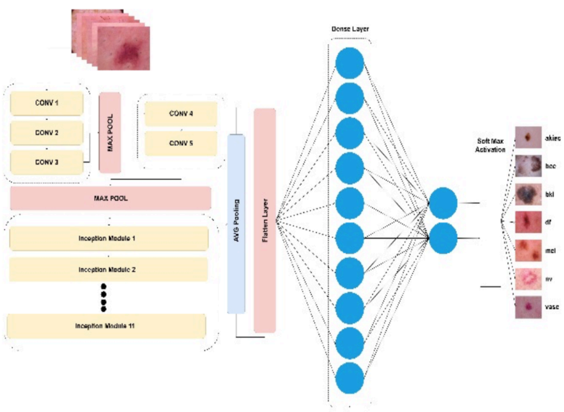

Fig. 8: Inception V3 Architecture presented in Amin *et al.* (2024)

Inception v3

The Inception V3 model belongs to the Inception series of convolutional neural network architectures, which were developed by researchers at Google (Amin *et al.*, 2024). It represents an evolution from the original Inception architecture, incorporating several key enhancements to improve efficiency and accuracy. One notable improvement in Inception v3 is the adoption of factorized convolutions (Amin *et al.*, 2024). This technique breaks down standard convolutions into smaller operations, reducing computational complexity and enhancing efficiency. Additionally, Inception v3 introduces various other techniques such as batch normalization, label smoothing, and auxiliary classifiers to enhance training stability and overall performance. Figure 8 illustrates the architecture of Inception V3, as referenced in Amin *et al.* (2024).

GoogleNet

The GoogleNet model is part of the Inception series of convolutional neural network architectures developed by researchers at Google (Aljohani & Turki, 2022). Building upon earlier iterations, GoogleNet introduced several key improvements to enhance efficiency and accuracy. One significant innovation is the use of factorized convolutions, which decompose standard convolutions into smaller operations to reduce computational complexity and boost efficiency. Additionally, GoogleNet incorporates techniques such as batch normalization, label smoothing, and auxiliary classifiers, all of which contribute to improved training stability and overall performance.

ViT

A new architecture termed Vision Transformer (ViT) has arisen for computer vision applications, motivated by the success of transformers in natural language processing (Cirrincione *et al.*, 2023). ViT breaks down images into smaller patches, similar to how text is divided into words. These patches are then processed by a transformer encoder, which analyzes the relationships between them to extract meaningful information.

Unlike traditional convolutional neural networks that rely on specific filters, ViT employs a mechanism called multi-head self-attention (Cirrincione *et al.*, 2023). This allows ViT to capture both local details within a patch and the broader context of how different patches relate to each other, regardless of the image's overall size or resolution. This flexibility makes ViT adaptable to various datasets and tasks. Notably, ViT has achieved competitive performance in image classification, object detection, and segmentation tasks, rivaling traditional convolutional neural networks (Cirrincione *et al.*, 2023). Vision Transformer architecture is shown in Figure 9.

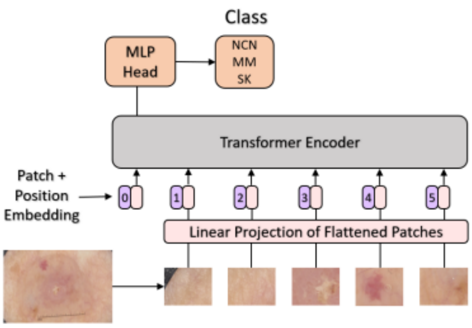

Fig. 9: ViT architecture presented in Cirrincione *et al.* (2023)

Deep Learning for Skin Cancer Classification

A summary of a recently released study that looks at the use of deep learning models for skin cancer diagnosis is given in this section.

A deep spiking neural network, which is particularly noteworthy for its energy efficiency and remarkable performance in the domain of skin cancer classification, was used to offer a unique technique by Qasim Gilani *et al.* (2023). Skip connections are incorporated into their Spiking VGG-13 model, which enables the network to learn complex features more efficiently and achieve higher accuracy than traditional deep neural networks like VGG-13 and AlexNet. Their comparative analysis showed that the Spiking VGG-13 performs better than these models, indicating its potential to improve dermatological diagnostic skills. Convolutional spiking neural networks trained using unsupervised Spike-Timing-Dependent Plasticity (STDP) (Zhou *et al.*, 2020) learning were employed in a different study to differentiate between melanoma and melanocytic nevi. Their accuracy rate was 83.8% on average, and it increased to 87% when feature selection approaches were used. This paper highlights the effectiveness of spiking neural networks in medical image processing applications, especially when complex feature extraction and classification are needed.

The modules in the proposed XceptionNet design, as depicted in Figure 10, match those in the original Xception model. Lu & Firoozeh Abolhasani Zadeh (2022) suggested enhancements to the XceptionNet. To improve its performance on the MNIST skin cancer dataset, the Swish activation function has taken the place of the ReLU activation function. It is positioned before the logistic regression and after the global average pooling. Swish activation functions are integrated with depthwise separable convolutions. Their adjustments produced notable gains over the first CNN design, Xception, and other CNN architectures, proving the value of creative architectural changes in obtaining better categorization outcomes. Comparative analysis of deep learning and machine learning models emphasized the critical role of dataset balance in influencing model efficacy for skin cancer classification tasks (Bechelli & Delhommelle, 2022). After a comprehensive study of many CNN architectures by Aljohani & Turki (2022), GoogleNet was found to be the best-performing model with a test set accuracy of 76.08%. Their thorough comparison helped shape future research paths in medical image analysis by illuminating the advantages and disadvantages of various CNN designs. Rashid *et al.* (2022) introduced a transfer learning technique using MobileNetV2, achieving exceptional diagnostic accuracy of 98.2% in skin lesion classification. Fraiwan & Faouri (2022) explored deep transfer learning approaches for melanoma classification, highlighting the challenges posed by dataset imbalance and the effectiveness of preprocessing methods in improving overall accuracy.

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Tyagi *et al.* (2022) proposed a convolutional neural network architecture with integrated data augmentation strategies, achieving high classification accuracies on the HAM10000 database using DenseNet201. Bassel *et al.* (2022) introduced a hybrid deep learning approach incorporating stacked cross-validation, which achieved an impressive accuracy of 90.0% by integrating multiple feature extraction methods and classification models.

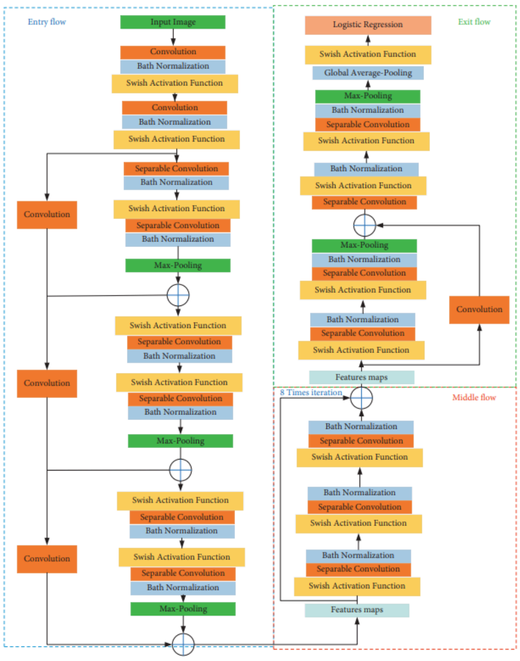

Fig. 10: XceptionNet architecture proposed in Lu & Firoozeh Abolhasani Zadeh (2022)

Kousis *et al.* (2022) extensive experimentation with 11 CNN architectures identified DenseNet169 as the top performer in dermatological image classification tasks, leveraging techniques such as data augmentation, transfer learning, and fine-tuning to address dataset challenges effectively. Jaisakthi *et al.* (2023) introduced EfficientNet, achieving an impressive AUC score of 0.9174 by implementing data augmentation and metadata utilization to address dataset class imbalances. They further optimized model efficiency through the ranger optimizer, minimizing hyperparameter tuning needs, thereby enhancing network performance and reliability in image classification. Imran *et al.* (2022) combined VGG, CapsNet, and ResNet into an ensemble model that achieved 93.5% accuracy, particularly excelling in sensitive applications like cancer detection, showcasing the collective decision-making strengths of individual learners for superior prediction accuracy. Naeem *et al.* (2022) proposed SCDNet, outperforming ResNet, Inception v3, AlexNet, and Vgg19 with an accuracy of 96.91%, leveraging a CNN-based network built upon Vgg16 for multi-class skin cancer classification from dermoscopy images. Ali *et al.* (2021) developed a DCNN model reaching 93.16% accuracy on the HAM10000 dataset, emphasizing robust preprocessing, including noise removal and normalization, along with data augmentation techniques to enhance classification performance. Khan *et al.* (2021) employed an Integrated Morphological Filtering Operator (IMFO) achieving up to 98.70% accuracy across various datasets through advanced segmentation and deep learning techniques, underscoring its effectiveness in automated lesion analysis and classification. Kausar *et al.* (2021) focus on ensemble models yielded accuracies of 98% and 98.6% by integrating ResNet, InceptionV3, DenseNet, InceptionResNetV2, and VGG-19 architectures, demonstrating the ensemble's capability to enhance classification accuracy significantly. Jain *et al.* (2021) explored transfer learning methods for multi-class skin cancer classification, highlighting Xception Net with an accuracy of 90.48% as the top performer among six evaluated architectures, emphasizing the efficacy of transfer learning in boosting accuracy and reliability. Jain *et al.* (2021) introduced a smartphone application integrating CNNs and a Differential Evolution algorithm, achieving 85% accuracy and demonstrating potential in enhancing diagnostic capabilities for skin cancer detection. Alazzam *et al.* (2021) assessed machine learning algorithms and reported a sensitivity of approximately 93% using the random forest classifier, focusing on attribute selection and data imbalance handling to improve classification performance. Saravana Kumar *et al.* (2021) achieved a detection accuracy of 97% for melanoma stages using a fusion-based deep learning approach, outperforming traditional methods like Random Forest and Support Vector Machine, highlighting significant advancements in melanoma detection accuracy.

Papiththira & Kokul (2021) introduced a novel CNN architecture leveraging EfficientNet for melanoma detection, achieving significant accuracies of 84.12% and 96.32% on UMGC and HAM10000 datasets, respectively. Their approach emphasizes deep transfer learning directly from raw images, enhancing detection speed with fewer samples by utilizing pre-trained models. They integrated a channel attention module to enhance melanoma-specific features during classification, demonstrating substantial performance improvements over existing methods. Junayed *et al.* (2021) proposed a deep CNN model that achieved an accuracy of 95.98%, surpassing models like GoogleNet and MobileNet. Islam *et al.* (2021) focused on melanoma classification, achieving 96.10% and 90.93% accuracies in training and testing, respectively, by applying CNN with comprehensive image preprocessing steps. Their method included data augmentation, normalization, and interpolation to distinguish benign and malignant lesions effectively. Patil & Bellary (2022) introduced an efficient CNN algorithm for melanoma stage detection, using SMTP as a specialized loss function to enhance accuracy significantly. Zhang *et al.* (2020) optimized a CNN-based approach with an enhanced whale optimization

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algorithm, demonstrating superior performance across datasets. Vidya & Karki (2020) developed a hybrid feature extraction methodology integrating machine learning techniques, which effectively enhanced skin lesion analysis. Their approach focused on preprocessing to improve image quality by mitigating artifacts like skin color and hair, employing the ABCD scoring method for extracting symmetry, border characteristics, color variations, and lesion diameter. They utilized Histogram of Oriented Gradients (HOG) and Gray-Level Co-occurrence Matrix (GLCM) techniques to extract textural features. Achieving a remarkable accuracy of 97.8% with Support Vector Machine (SVM) classifiers underscores the efficacy of their method in dermatological image analysis for clinical applications. Similarly, Manasa *et al.* (2020) aimed to enhance skin cancer classification precision, employing a Gaussian Filter to reduce image noise and enhanced K-means clustering for lesion segmentation. Their innovative approach integrated textural and color features into a hybrid super feature vector, achieving 96% accuracy in distinguishing melanoma and nevus skin cancer types using SVM classifiers. Wang & Zhang (2020) introduced a DenseNet-201-based method for multiple sclerosis classification, leveraging Composite Learning Factor (CLF) strategies to optimize neural network layer allocation. Their findings highlighted DenseNet-201-D as superior, achieving high sensitivity, specificity, and accuracy, demonstrating the efficacy of deep learning in medical image analysis. Thurnhofer-Hemsi & Domínguez (2021) utilized DenseNet201 effectively in dermatological image analysis, emphasizing its capability to reduce false negatives and enhance diagnostic accuracy, particularly through initial binary classification between nevi and non-nevi lesions.

Continuing the exploration of innovative approaches to skin cancer detection and classification, Hartanto & Wibowo (2020) utilize FR-CNN and MobileNet V2 models, achieving significant accuracies of 87.2% and 86.3% respectively, with Faster R-CNN outperforming MobileNet V2. This research underscores the potential of these deep learning techniques in enhancing diagnostic accuracy in dermatological applications. Banerjee *et al.* (2020) introduces a novel approach using the YOLO model for melanoma detection, demonstrating superior accuracy and efficiency compared to traditional CNNs, particularly with a high Jac score on the ISBI 2017 dataset. Rezaoana *et al.* (2020) proposes an automated method for skin cancer classification using transfer learning, achieving approximately 79.45% accuracy, enhanced by image augmentation techniques. Ottom (2019) presents a computational method for predicting new types of skin cancers using a CNN with an accuracy of 74%, utilizing advanced image preprocessing and a robust CNN architecture.

Adegun & Viriri (2020) introduces a deep learning system for melanoma classification and segmentation, achieving 95% accuracy and a 92% dice coefficient on the ISIC 2017 dataset, highlighting the efficacy of their multi-stage and multi-scale approach, Figure 11 illustrates the proposed architecture and the key stages from image preprocessing to feature extraction, pixel-wise classification, and ultimately lesion classification. The input is processed by the encoder sub-network initially, and features are subsequently extracted using the decoder. Next, a second module uses a combination of the dice loss function and the softmax classifier to determine the region of interest for melanoma and categorize the images pixel by pixel. Through a mix of image preprocessing approaches and machine learning algorithms, Khan *et al.* (2019) describes an intelligent system for melanoma detection and nevus categorization utilizing a support vector machine, attaining 96% accuracy. An overview of the developments in deep learning for skin cancer diagnosis is given by Pacheco & Krohling (2019), who also highlight the incorporation of cellphones and potential directions for further study. Chung & Sapiro (2000) suggest a method for skin lesion segmentation that makes use of partial differential equations, improving the precision of border detection and segmentation in digital clinical pictures. In a thorough analysis of CNN models for dermoscopy skin cancer diagnosis, Rezvantalab *et al.* (2018) found that DenseNet 201 scored highly on datasets such as HAM10000 and PH2, with averaged AUC values of 98.16% and 98.79%, respectively.

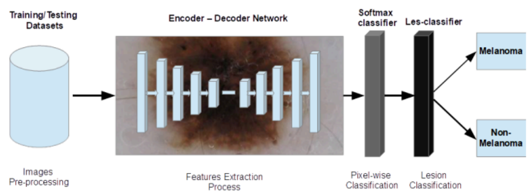

Fig. 11: Deep Convolutional Encoder-Decoder Networks architecture proposed in Adegun & Viriri (2020)

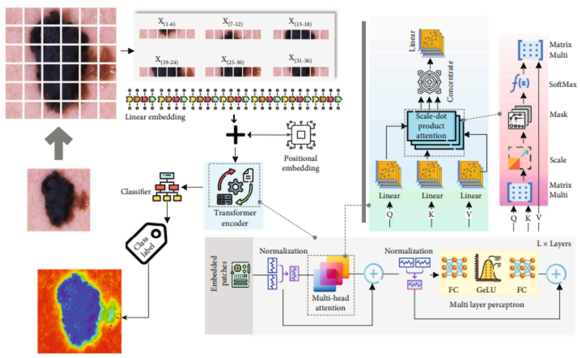

Fig. 12: ViT-Google architecture proposed in Himel *et al.* (2024)

ViT-Google shows how vision transformers (ViT)can outperform traditional CNNs (Himel *et al.*, 2024); the suggested ViT-Google's architecture is shown in Figure 12. One such architecture to be used is one that combines

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a vision transformer-based network and a CNN-based network together. However, the vision transformer architecture has a number of advantages: Compared to CNNs, ViT models employ self-attention to more accurately capture the long-range relationships of the input images. It is feasible to discover the contextual connections between different patches, which will enable ViT to better understand global image structures.

The same would further benefit tasks whose performance relies on modeling long-range dependencies. As a result, this won't require any changes to the architecture to handle photos of different resolutions. ViT-Google's accuracy on the HAM10000 dataset was 96.95%, demonstrating their capacity to use attention processes to detect global relationships in pictures. With an accuracy of 93.75% and a sensitivity of 88.07% in the ISIC 2020 competition, the DDCNN model demonstrated impressive performance, highlighting the significance of creative network architectures and cutting-edge data augmentation methods in enhancing skin cancer diagnosis (Veeramani *et al.*, 2024). With accuracies of 97.48% on ISIC 2019 and 96.87% on the PH2 dataset, the optimized ResNet variant OptResNet-18 demonstrated the importance of optimized CNN architectures for accurate skin lesion classification (Rezaee & Zadeh, 2024).

SNC-Net, evaluated on the ISIC 2019 dataset, achieved a high classification accuracy of 97.81% by combining deep learning and handcrafted feature extraction techniques, thereby enhancing overall classifier performance (Naeem *et al.*, 2024). As illustrated in Figure 13, the architecture of SNC-Net begins with data preprocessing, followed by dual-stream feature extraction using InceptionV3 and handcrafted (HC) features. These extracted features are then fused and passed through a convolutional neural network (CNN) for final classification. DVFNet with SMOTE TOMEK attaining an accuracy of 98.32% on ISIC 2019, highlighted the impact of advanced data augmentation techniques in enhancing model performance for skin cancer detection (Naeem & Anees, 2024).

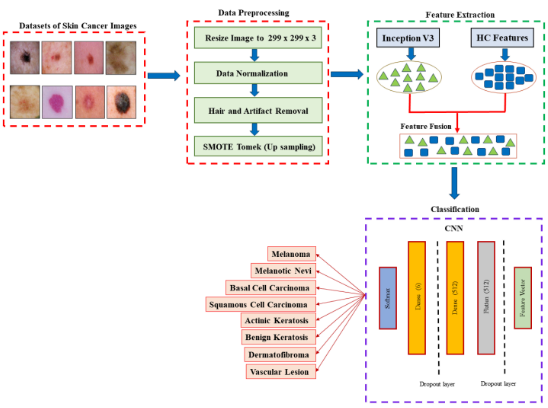

Fig. 13: SNC-Net architecture proposed in Cirrincione *et al.* (2023)

ConvNexTBase further demonstrated the efficacy of CNN architectures with a remarkable accuracy of 99% on ISIC 2019 (Abou Ali *et al.*, 2024). The ensemble method combining MobileNet and DenseNet achieved a balanced accuracy of 93.75% on ISIC 2019, showcasing the prospects of ensemble learning in dermatological image classification (Imam *et al.*, 2024). EfficientNetB0 combined with a nature-inspired feature optimization algorithm, achieved a notable accuracy of 98% on ISIC 2018, highlighting the efficacy of SVM-based approaches in skin cancer classification (Imran *et al.*, 2024). Using lightweight CNNs with transfer learning, Eatedal Alabdulkreem's study achieved 91% accuracy on HAM10000, highlighting the benefits of utilizing pre-trained models for skin lesion categorization (Alabdulkreem *et al.*, 2024). Maaz Ul Amin's study, utilizing Inception V3, achieved a remarkable diagnostic accuracy of 99.80%, demonstrating the potential of sophisticated deep learning architectures in improving automated medical diagnosis systems (Amin *et al.*, 2024).

Datasets

The most commonly used datasets in skin cancer diagnosis are provided in the sections below.

HAM10000

The HAM10000 dataset, comprising 10,015 dermoscopic images, serves the purpose of identifying pigmented skin lesions (Ali *et al.*, 2021). These images were sourced from diverse populations and captured using various methods before being stored. The dataset includes 142 vascular skin lesion images, 327 images of AK, 514 basal cell carcinoma images, 1099 benign keratosis images, 115 dermatofibroma images, 1113 melanocytic nevi images, and 6705 melanoma images. Access to this dataset is available to the public via the ISIC archive (Ali *et al.*, 2021; Islam *et al.*, 2021; Thurnhofer-Hemsi & Domínguez, 2021; Hamida *et al.*, 2024).

PH²

A dermoscopic image database, known as PH², has been created specifically for research and benchmarking purposes. This is used to facilitate the comparative study of classification and segmentation algorithm of dermoscopic images (Banerjee *et al.*, 2020; Alazzam *et al.*, 2021).

ISIC

The ISIC datasets have emerged as a primary resource for machine learning researchers focusing on analyzing medical images, particularly in the field of skin cancer detection (Hartanto & Wibowo, 2020).

ISIC2016

The ISIC 2016 dataset is a comprehensive collection of dermatoscopic snapshots, comprising numerous sorts

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of pores and skin lesions such as melanoma, nevi, and basal mobile carcinoma. These snapshots are meticulously curated to function as a treasured resource for the improvement and assessment of computerized pores and skin lesion classification algorithms. Researchers and clinicians can leverage this dataset to strengthen the field of dermatology by creating innovative answers for early detection and diagnosis of pores and skin cancers. With its various range of extremely good pics and accompanying annotations, the ISIC 2016 dataset performs a crucial role in improving the accuracy and reliability of computer-aided diagnostic systems, in the long run contributing to improved patient outcomes and healthcare transport (Naqvi *et al.*, 2023).

ISIC18

The ISIC 2018 dataset comprises more than 12,500 training photographs, along with a hundred validation data and a thousand test images, providing a vast collection for studies and analysis in dermatology and clinical image processing (Zhou *et al.*, 2020).

ISIC2019

In the ISIC 2019 collection, there are 25,331 data depicting 8 different forms of pores and skin lesions, starting from melanoma to benign keratosis, dermatofibroma, vascular lesions, and SCC (Naeem & Anees, 2024). Notably, the dataset capabilities an outlier class that was supposed to be part of the training data, and it encompasses 8239 images for the testing set. Furthermore, the ISIC2019 dataset includes valuable data metadata along with the patient's gender, age, and location (Naeem & Anees, 2024; Thanga Purni & Vedhapriyavadhana, 2024).

ISIC2020

The dataset consists of 33,126 dermoscopic image data portraying various malignant and benign images, sourced from the records of over 2000 individuals (Veeramani *et al.*, 2024).

PAD-UFES-20

The PAD-UFES-20 dataset presents a wealthy useful resource for developing and trying out algorithms for pores and skin lesion analysis (Jain *et al.*, 2021). Gathered by the Federal University of Espírito Santo (UFES) under Brazil's Dermatological and Surgical Assistance Program, the data includes pictures and medical details for more than 2300 pores and skin lesions. These lesions represent numerous kinds, such as not unusual pores and skin cancers like basal mobile carcinoma and melanoma, in addition to benign situations like seborrheic keratosis (Naeem & Anees, 2024).

Table 1: Exploring Deep Learning Methods for Skin Cancer Classification: A Comparative Analysis

Paper	Dataset	Algorithm	Results
Qasim Gilani *et al*. (2023)	ISIC 2019	spiking VGG-13	Accuracy: 89.57% F1 score: 90.07%
Zhou *et al*. (2020)	ISIC 2018	STDP-Based Convolutional SNNS	Accuracy: 83.91% F1 score: 85.79%
Lu & Firoozeh Abolhasani Zadeh (2022)	HAM10000	Xception	Accuracy: 100% F1 score: 95.53%
Bechelli & Delhommelle (2022)	HAM10000	VGG16	Accuracy: 88% F1 score: 88%
Aljohani & Turki (2022)	ISIC 2019	GoogleNet	Accuracy: 76%
Rashid *et al*. (2022)	ISIC 2020	MobileNetV2	Accuracy: 98.2% F1 score: 98.1%
Fraiwan & Faouri (2022)	HAM10000	Transfer Learning	Accuracy: 82%
Tyagi *et al*. (2022)	HAM10000	CNN	Accuracy: 97.8% F1 score: 98.1%
Bassel *et al*. (2022)	ISIC 2019	StackingCV	Accuracy: 90% F1 score: 89.8%
Kousis *et al*. (2022)	HAM10000	DenseNet169	Accuracy: 92.5% F1 score: 93.27%
Jaisakthi *et al*. (2023)	ISIC 2020	DCNN-EfficientNet-B6	Accuracy: 96.8%
Imran *et al*. (2022)	ISIC 2019	Ensembled VGG, ResNet,CapsNet	Accuracy: 93% F1 score: 92%
Naeem *et al*. (2022)	ISIC 2019	SDCNet	Accuracy: 96.91% F1 score: 97.24%
Ali *et al*. (2021)	HAM10000	DCNN	Accuracy: 90.61% F1 score: 94.27%
Khan *et al*. (2021)	HAM10000	CNN	Accuracy: 90.6%
Kausar *et al*. (2021)	ISIC 2018	Ensemble Fine-Tuned DL Models	Accuracy: 98.6% F1 score: 97%
Angelina & Ulfitria (2024)	Dermatoscopic Skin Cancer	VGG16	Accuracy: 83.75% F1 score: 84%
Jain *et al*. (2021)	HAM10000	Xception Net	Accuracy: 90.48% F1 score: 90%
Krohling *et al*. (2021)	PAD-UFES-20	ResNet50	Accuracy: 85% F1 score: 87.07%
Alazzam *et al*. (2021)	PH2	VGG Feature and GS algorithms Random Forest	Accuracy: 92% Sensitivity: 93%
Saravana Kumar *et al*. (2021)	HAM10000	DCNN	Accuracy: 97% RMSE: 0.56%
Papiththira & Kokul (2021)	UMGC and HAM10000	EfficientNet-B3	Accuracy: 84.12% Accuracy: 96.32%
Junayed *et al*. (2021)	Self collected	MobileNet	Accuracy: 95.98% Sensitivity: 91.97%
Islam *et al*. (2021)	HAM10000	CNN	Accuracy: 90.93% F1 score: 94.73%
Patil & Bellary (2022)	Melanoma Dataset	CNN with SMTP	Accuracy: 92% F1 score: 92.2%
Vidya & Karki (2020)	ISIC 2019	HOG+GLCM+SVM	Accuracy: 97.8% AUC: 0.94%

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Table 1: Continued

Paper	Dataset	Algorithm	Results
Manasa *et al*. (2020)	DERMIS	SVM	Accuracy: 96%
Wang & Zhang (2020)	MIT-BIH	DenseNet-201-D	Accuracy: 98.31% F1 score: 98.30%
Srividhya *et al*. (2020)	DermIS	CNN	Accuracy: 95% Sensitivity: 93.3%
Thurnhofer-Hemsi & Domínguez (2021)	HAM10000	DenseNet201	Accuracy: 95.09% F1 score: 92.51%
Hartanto & Wibowo (2020)	ISIC 2019	Faster R-CNN	Accuracy: 87.2%
Banerjee *et al*. (2020)	PH2	YOLO	Accuracy: 99% IOU: 0.99
Rezaoana *et al*. (2020)	ISIC 2017	CNN	Accuracy: 79.45% F1 score: 76.9%
Ottom (2019)	ISIC 2017	CNN	Accuracy: 74%
Adegun & Viriri (2020)	PH2	DCEDN	Accuracy: 95% Dice score: 93
Khan *et al*. (2019)	DERMIS	GLCM,LBP,SVM	Accuracy: 96% Sensitivity: 97
Rezvantalab *et al*. (2018)	HAM10000	DenseNet 201	ROC AUC: 99.3% F1 score: 89.1%
Hamida *et al*. (2024)	HAM10000	RF + DNN	Accuracy: 96.8%
Himel *et al*. (2024)	HAM10000	ViT-Google	Accuracy: 96.95% F1 score: 96.12%
Veeramani *et al*. (2024)	ISIC 2020	DDCNN	Accuracy: 93.75% Sensitivit: 88.07%
Rezaee & Zadeh (2024)	ISIC 2019, PH2	optResNet-18	Accuracy: 97.48% F1 score: 97.51%
Cirrincione *et al*. (2023)	ISIC 2019	ViT	Accuracy: 94.8% Sensitivity: 92.8%
Naeem *et al*. (2024)	ISIC 2019	SNCNet	Accuracy: 97.81% F1 score: 98.10%
AlSadhan *et al*. (2024)	ISIC 2019	YOLOv7	IOU: 89.8% F1 score: 82.1%
Mushtaq & Singh (2024)	HAM10000	CNN	Accuracy: 88% F1 score: 89%
Naeem & Anees (2024)	ISIC 2019	DVFNet with SMOTE TOMEK	Accuracy: 98.32% F1 score: 98.19%
Abou Ali *et al*. (2024)	ISIC 2019	ConvNexTBase	Accuracy: 99% F1 score: 91%
Thanga Purni & Vedhapriyavadhana (2024)	ISIC 2019	CNN-EOSA	Accuracy: 89.57%
Imam *et al*. (2024)	ISIC 2019	Ensemble Method MobileNet+DenseNet	Accuracy: 93.75% F1 score: 68%
Alabdulkreem *et al*. (2024)	HAM10000	LWCNN	Accuracy: 91% F1 score: 92
Imran *et al*. (2024)	ISIC 2018	CB-SVM	Accuracy: 98% F1 score: 98.47%
Amin *et al*. (2024)	HAM10000	Inception V3	Accuracy: 82.27% F1 score: 65

Discussion

The review is done on different deep learning models for skin lesion classification and detection, revealing that CNNs, Vision Transformers (ViTs), and ensemble models tend to perform better in comparison to other methods. Each model has its own set of advantages and limitations that impact their effectiveness in different scenarios.

Strengths and Limitations of Different Algorithms

Each algorithm reviewed in this paper exhibits unique strengths and weaknesses that impact its effectiveness in skin cancer detection. For instance, Convolutional Neural Networks (CNNs) have been widely adopted due to their powerful feature extraction capabilities, which are crucial for accurate image analysis. However, they often require extensive computational resources and large amounts of labeled data. Vision Transformers (ViTs) and Spiking VGG-13 models have shown promise in handling complex image patterns and achieving high accuracy, but they also demand substantial computational power and may suffer from overfitting if not properly regularized.

Ensemble methods, which combine multiple models, have emerged as a robust approach to enhance classification performance. Ensemble approaches reduce the drawbacks of individual models by combining the advantages of several algorithms, improving accuracy and generalization. Hybrid approaches that integrate traditional machine learning techniques with deep learning models also show potential in refining the classification process.

The Role of Preprocessing and Image Augmentation

Preprocessing and image augmentation are critical stages in the skin cancer detection pipeline. Effective preprocessing techniques, such as noise reduction and contrast enhancement, are essential for improving the quality of input images, thereby facilitating more accurate analysis. Image augmentation techniques, including rotation, scaling, and flipping, help in diversifying the training data, lowering the possibility of overfitting, and improving the model's capacity to adapt to new unseen data.

Data balance is another crucial factor to take into account, particularly when it comes to medical image analysis when a dataset can have an exceptionally high proportion of benign vs malignant cases. By correcting for this imbalance, methods like as oversampling the minority data and undersampling the majority data can improve the model's performance on underrepresented classes.

Transfer Learning and Its Benefits

Transfer learning has proven to be a valuable technique, especially in scenarios with limited annotated data. By leveraging pre-trained models like VGG16, MobileNetV2, and DenseNet201, researchers can transfer knowledge from large, diverse datasets to

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specific tasks like skin cancer detection. This approach not only reduces the need for extensive labeled data but also accelerates the training process and often leads to improved performance. The success of transfer learning highlights the importance of utilizing large-scale datasets and domain-specific features for enhanced generalization and accuracy.

Innovations in Model Architecture

Innovations in model architecture, such as the use of skip connections and self-attention mechanisms, have further contributed to the advancements in skin cancer detection. Skip connections help in mitigating the vanishing gradient problem, allowing deeper networks to be trained effectively. Self-attention mechanisms, as used in Vision Transformers (ViTs), enable the model to focus on relevant parts of the image, leading to more accurate feature extraction and classification.

Performance Across Different Datasets

In this research, we examined how various machine learning models perform across a diverse array of datasets in the realm of skin lesion classification. Our investigation covered datasets like ISIC, HAM10000, PH2, DERMIS, and additional sources. As illustrated in Figure 14, our analysis reveals that among these datasets, HAM10000 is particularly noteworthy for its extensive compilation of dermatoscopic images, presenting a valuable resource for training and assessing classification models. Models trained on HAM10000 achieved notable accuracies, with approaches like Transfer Learning, DenseNet, and CNN exhibiting competitive performance (Thurnhofer-Hemsi & Domínguez, 2021). Notably, Xception (Lu & Firoozeh Abolhasani Zadeh, 2022) achieved an accuracy of 99%, showcasing the effectiveness of deep learning architectures on this dataset (Figure 15). Moving beyond HAM10000, ISIC datasets present unique challenges due to variations in imaging conditions and lesion types. Our results indicate promising performances on ISIC datasets, with models such as Spiking VGG-13 (Qasim Gilani *et al.*, 2023), MobileNetV2 (Rashid *et al.*, 2022), and DDCNN (Jaisakthi *et al.*, 2023) achieving accuracies exceeding 90%. However, it's crucial to note the variance in model performance across ISIC datasets, with accuracies ranging from 76% to 98.6%. The accuracy of each model over the ISIC dataset is depicted in Figures 16, 17 and 18. This underscores the importance of dataset-specific model tuning and exploration (Vidya & Karki, 2020; Kausar *et al.*, 2021). Additionally, our study explored datasets like PH2 (Alazzam *et al.*, 2021) and DERMIS (Khan *et al.*, 2019), which offer smaller but valuable collections of dermatoscopic images. In Figure 19, for the PH2 dataset, the models, despite the relatively small size of the dataset, demonstrated competitive performance. Algorithms such as VGG-based feature extraction combined with GS algorithms like Random Forest achieved an accuracy of 92% on the PH2 dataset (Alazzam *et al.*, 2021). Additionally, for lesion detection, the YOLO algorithm attained a remarkable accuracy of 99% with an Intersection over Union (IoU) score of 0.99. In Figure 20 for the DERMIS dataset the Xception model achieved perfect accuracy (100%) and an F1 score of 95.53, outperforming other models like STDP-Based Convolutional SNNS and VGG16, which showed good but relatively lower performance.

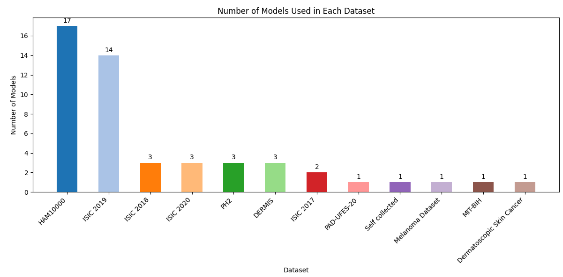

Fig. 14: Dataset used for the experiments

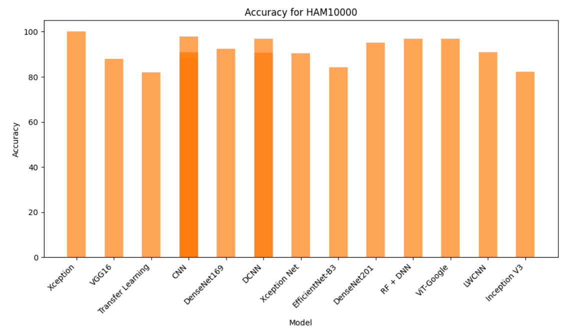

Fig. 15: Accuracy of models using the HAM10000 dataset

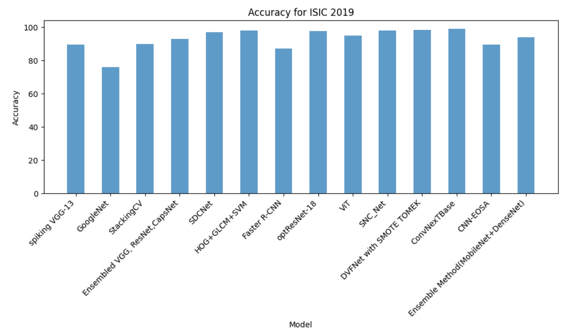

Fig. 16: Accuracy of models using the ISIC 2019 dataset

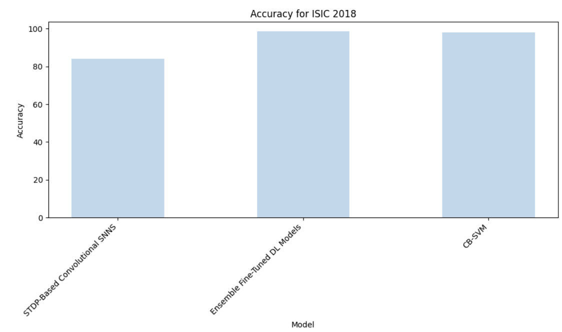

Fig. 17: Accuracy of models using the ISIC 2018 dataset

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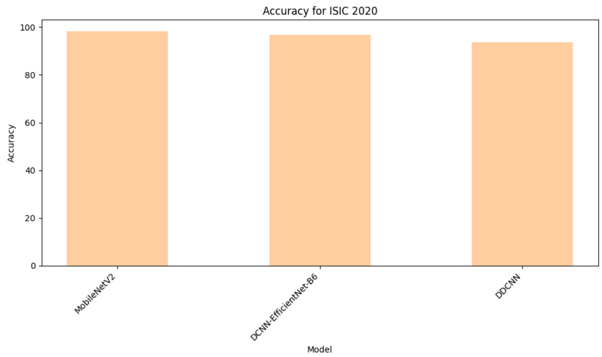

Fig. 18: Accuracy of models using the ISIC 2020 dataset

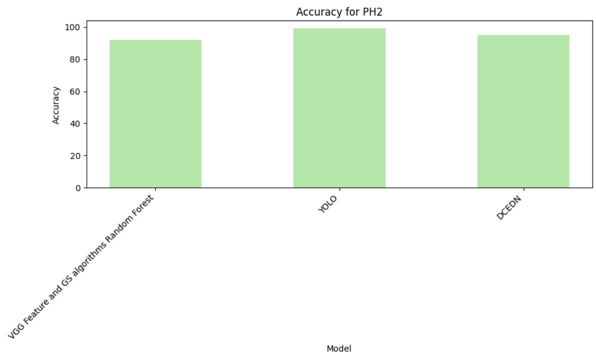

Fig. 19: Accuracy of models using the PH2 dataset

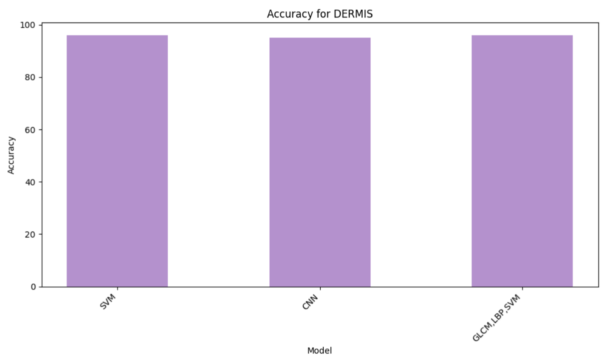

Fig. 20: Accuracy of models using the DERMIS dataset

Conclusion

This systematic review highlights the significant progress made in using neural network algorithms for the noninvasive detection and classification of skin cancer. Through a detailed analysis of Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), and ensemble models, we have identified the critical steps in the skin cancer detection pipeline, including preprocessing, image augmentation, segmentation, feature extraction, selection, and classification.

Each algorithm reviewed presents unique strengths and weaknesses, necessitating careful selection to achieve optimal results. Notably, deep learning algorithms, particularly Spiking VGG-13, EfficientNet, and ViT-Google, have demonstrated exceptional accuracy in distinguishing between benign and malignant lesions across various datasets. Ensemble methods and hybrid approaches have emerged as promising strategies to further enhance classification performance. Additionally, transfer learning techniques, leveraging pre-trained models such as MobileNetV2 and DenseNet201, have proven invaluable, especially in scenarios with limited annotated data, underscoring the importance of utilizing large-scale datasets and domain-specific features for improved generalization.

Despite the advances, current research predominantly focuses on classifying individual lesion images as cancerous or not without addressing broader diagnostic questions, such as the presence of specific skin cancer symptoms across the entire body. Future research should expand to include autonomous full-body image capture and detection, addressing a crucial gap in current methodologies. Furthermore, the emerging concept of auto-organization within deep learning, which involves unsupervised learning techniques to identify features and discover patterns, shows promise. Though still in the research and development phase, auto-organization could significantly enhance the accuracy of medical imaging systems by capturing minute details crucial for accurate diagnosis. This advancement could be particularly impactful in medical imaging, where precision is paramount for correct disease identification.

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Authors Contributions

Goutham Lal Shanmughamadom Harilal: Collected and analyzed the data, prepared figures and tables, and drafted the manuscript.

Tamilselvi Panneerselvam: Provided supervision, critical review, and final approval of the manuscript for publication.

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