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A statistical review of skin disease detection models for different skin-tones

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Abstract: *Variations in the body's melanin synthesis are one of the most important factors that contribute to the development of skin diseases. As a consequence of these abnormalities, a variety of skin illnesses, including but not limited to acne, psoriasis, eczema, vitiligo, ichthyosis, and seborrheic dermatitis, may develop. Each of these illnesses manifests itself in a manner that can be seen on a person's body, making it possible to diagnose each of them using image processing methods. Scientists have developed a variety of models to represent the real workings of image processing throughout the years. Convolutional neural network (CNN), evolving fuzzy classification, constrained-syntax genetic programming, and the Naive Bayesian classifier are examples of models that belong to this group (NB). However, these models do not account for a variety of characteristics, such as geographical differences, the effect of age on the skin, gender, skin tone, skin type, and other comparable aspects when making judgments. This has led to the evaluation of a number of stratification models for skin disorders, which is discussed in this particular piece of literature. In addition, the model now incorporates performance metrics for precision, computational complexity, scalability, and other parametric adjustments. Researchers and skin care professionals are encouraged to use this knowledge to discover the algorithmic combination that is most advantageous for a particular application. Consequently, the building of a high-performance system for classifying skin illnesses and the rapid development of apps will be made feasible. Various system models, such as high-performance approaches for feature extraction and selection, illness stratification, skin segmentation, and more, may also be used. There are several system models from which to pick. This article employs a multiparametric approach, which takes into account a range of variables, such as a person's skin tone and geographical characteristics. In order to categorize the analysed algorithms, these criteria and other performance indicators are reviewed and considered. In addition, this study provides recommendations for enhancing current models via algorithmic fusion, model enhancement, incremental learning, and related approaches. The readers of this post will be able to apply these enhancements, which will improve the functionality of existing systems in a variety of use cases.*

Keywords: *Dermatology, Skin Disease, Cancer, Machine Learning, CNN.*

INTRODUCTION

For skin condition categorization, multidomain image processing is necessary. This activity begins with the collection of image data, followed by feature extraction, feature selection, classification, and post-processing. If the goal is to create a stratification model for skin conditions that is capable of achieving high levels of performance, each of these processes must be executed with the greatest care. Figure 1 depicts a model that may be used to describe these phenomena in a more broad fashion. The input picture collection is then separated into two groups for testing and training. The training set, which is used by the model to train the classifier, consists of photos of different skin states as well as the corresponding skin conditions. The model utilizes the training set. During the training phase, the input images are pre-processed to eliminate noise and undergo a variety of further modifications. This is done in preparation for the learning phase. Histogram equalization, contrast correction, sharpness variation, and a few other types of improvements are examples of these modifications.

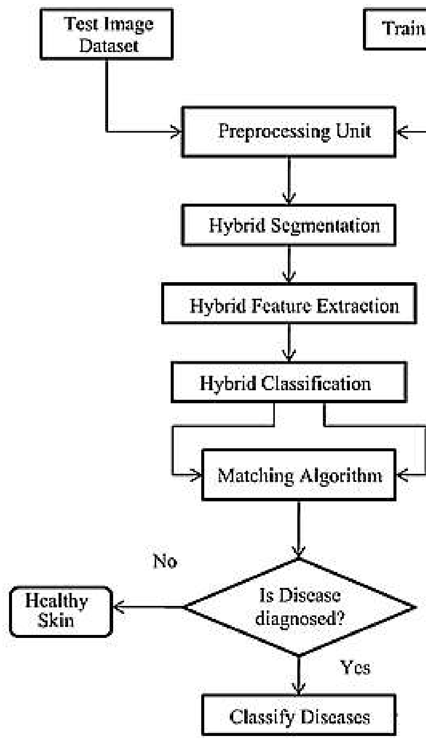

Figure 1. A typical model for skin disease classification purposes

When applied to pre-processed pictures, a segmentation model could utilize a variety of methods, such as saliency maps, fuzzy C means (FCM), loosely connected convolutional neural network (LC2NN), and others. These methods are used in order to break down a picture into its constituent pieces. The primary objective of this section is to eliminate all other components of the picture, with the exception of the injured skin, in order to generate an entirely new image that retains none of the undesirable qualities that were present in the original. The information is then recovered from the output picture via a feature extraction model, which includes methods such as independent component analysis (ICA), intrinsic moments (IMs), Fourier transforms, wavelet transformations, and a variety of other transformations. In order to make skin scans ready for categorization in the not-too-distant future, these attributes are used to turn them into one-dimensional numerical vectors. The primary goal of any feature extraction unit is to simultaneously raise the total amount of feature variation between photographs representing various states of the skin while concurrently lowering the degree of feature variation between images exhibiting the same condition. The efforts of the feature extraction models and the feature selection models working together make this procedure far simpler and less complicated than it would otherwise be. These models include a wide variety of different types of analyses, including mutual information, independent component analysis, principal component analysis, and bioinspired models, amongst others. They do this by reducing the amount of overlap that exists between different feature classes. This makes the stratification process more effective.

Following the completion of the attribute selection procedure, a matching algorithm is used in order to categorize the qualities that were chosen as belonging to one of "N" distinct skin disorders. Convolutional neural networks (CNN), recurrent neural networks (RNN), generative adversarial networks (GAN), long-short-term memory (LSTM), and a great number of other methodologies are used in order to make this a reality. In the section that is to come on this page, you will find an overview of numerous algorithms, as well as information on their particulars, as well as information on their benefits, advantages, limits, and downsides. After that, the models are subjected to statistical analysis in connection to a wide range of characteristics, such as regional variations, the kind of skin, the tone of skin, gender, age, group, and so on. Researchers and system designers will be able to choose the algorithmic configuration that is best suitable for the particular application on which they are currently working with the assistance of this study. This article draws to a close with a number of insightful observations on the models that are being evaluated, as well as a number of suggestions for improving the utility of those models.

IN DEPTH REVIEW OF DIFFERENT SKIN DISEASE IDENTIFICATION MODELS

Researchers provide many models for diagnosing skin disorders, each with its own functional subtleties, contextual benefits, application-specific restrictions, and future research goals. This section further segregates these models in terms of their internal operating characteristics. These include, deep learning methods, machine learning based techniques, low complexity techniques, and high scalability techniques, that can be applied to a wide variety of use cases.

Deep Learning Methods for identification of skin diseases

For example, deep learning has been used to medical imaging to identify skin problems [1]. A well-trained deep learning model may not be able to generalize to data from different cohorts due to domain shift. The problem cannot be solved by combining disease sample data from different data sources. Researchers describe two methods for cross-domain skin disease detection. Researchers investigate a two-step progressive transfer learning method using a fully supervised deep convolutional neural network classifier trained on ImageNet (CNN TSP TL). Researchers advise employing adversarial learning to achieve domain-invariant attribute translation from source to target in order to improve recognition performance. Using two skin image datasets from various clinical scenarios and cohorts with varied disease distributions, researchers analyze model generalization on melanoma diagnosis, cancer detection, and cross-modality learning to assess these two strategies. Their domain change method is effective, according to experiments.

There is a class imbalance in a number of categorization professions, claims [2]. The classification outcomes for minority groups with fewer training examples are biased. To address the discrepancy, the majority and minority classes are often resampled. For sorting data from several groups, the difficulty of distinguishing discrete categories is essential. Several rare skin conditions have few training samples, yet are easily recognized due to their aesthetic characteristics. Eczema is a common skin condition that has no obvious symptoms. SPBL is suggested by researchers as a remedy for this problem. The difficulty of the picture category is influenced by the sample size and identification challenges. The first-place approach, in which pace corresponds to one cycle of self-paced learning, introduces complexity initially. The training examples in the curriculum are rearranged by the researchers after each class is given a penalty weight. The model may regularly pick up discriminative representations with the right complexity balance. The suggested SPBL approach performs well with the benchmark data sets SD-198 and SD-260. Additionally, studies demonstrate the generalizability of SPBL for classifying objects and identifying interior situations.

In order to diagnose skin diseases, Deep Convolutional Neural Network (DCNN) [3] models have been developed extensively. Some of these models have shown diagnostic performance that is comparable to or even better than that of dermatologists. Skin lesion datasets that are unbalanced and small prevent DCNN from being widely used to identify skin diseases. This article offers a method for identifying skin lesions on small, imbalanced datasets using a single model. In the beginning, DCNNs are trained on small, imbalanced datasets to demonstrate that moderately challenging models outperform large ones. To address the underrepresentation of samples in the small dataset, modified Rand Augment is recommended. Drop Out and Drop Block are also given to reduce overfitting. To address unequal sample size and classification complexity, as well as to reduce the impact of anomalous data on training, a novel Multi-Weighted New Loss (MWNL) function and end-to-end cumulative learning strategy (CLS) are created. On datasets of dermoscopic images, researchers beat various ensembling models by combining Modified Rand Augment, MWNL, and CLS into a single DCNN model. Since it can achieve acceptable classification performance with minimal computational resources and inference time, their work shows that this method is appropriate for mobile devices in low-resource situations for automated screening of skin lesions and other cancers.

The precise diagnosis of malignant skin tumors is a vital goal due to the incidence and severity of skin cancer, especially as treatment is often advantageous if the tumor is found early. High-quality CAD system development is hampered by a lack of published histology image sets and an intuitive link between lesion characteristics and different forms of skin cancer. Based on real histology pictures accumulated over the last 10 years, DRANet [4], a framework for light-weight attention mechanism-based deep learning, is proposed to identify eleven different types of skin disorders. A visual diagnostic report with the name of the illness and any pertinent areas may be provided by the CAD system. The DRANet outperforms baseline models (InceptionV3, ResNet50, VGG16, and VGG19) in terms of performance and parameter size while offering comparable accuracy with fewer model parameters. Skin disease diagnosis is aided by the visual results from DRANet's hidden layers, which emphasize class-specific diagnostic spots.

Numerous skin ailments affect millions of Americans, according to study [5]. Unknown dangers that cause skin cancer, sadness, and poor self-esteem are often present in these diseases. Due to the poor visual resolution of these disorders' pictures in the past, skin disease identification required specialist technologies. Skin condition manual diagnosis is labor-intensive, subjective, and time-consuming. It is thus vital to develop a method for computer-assisted skin disease diagnosis. Most earlier studies on skin disorders used CNN with conventional loss functions, which restricted the model's capacity to learn distinctive characteristics from skin pictures. The problem was solved by applying a triplet loss function to fine-tune ResNet152 and InceptionResNet-V2 models. The suggested method initially embeds the input pictures in Euclidean space using CNN ResNet152 and InceptionResNet-V2. To determine the distinguishing characteristics of skin disease photos, the L-2 distance between similar images in Euclidean space is determined. Sort the provided photos into groups using L-2 distances. The proposed framework makes use of images of human faces with skin conditions acquired at Wuhan Hospital in China. Analyses and experiment results show how beneficial the proposed framework is for tasks involving skin diseases.

According to [6], many aspects of their life, including their health, are changing as a result of the Internet of Things' exponential expansion. Remote illness detection may be enhanced by sophisticated IoT systems that use intelligent IoT data processing and learning algorithms, for example. Skin issues are categorized on this page. With the use of IoT, this initiative seeks to provide remote skin disease diagnosis. Three distinct files comprise the study. Examples of IoT-Fog-Cloud remote diagnostic architecture with hardware may be found in the first folder. An evaluation survey of machine learning skin disease models may be found in the second folder. The evaluation is carried out using methods for data collection and processing. There are training-testing, cross-testing, and validations for each of the seven criteria. The HAM10000 dataset was also picked after comparisons with other relevant datasets. Six Deep Learning models are highlighted by this approach: VGG16, Inception, Xception, MobileNet, ResNet50, and DenseNet161. Prior ANN, SVM, and KNN models are explored in the assessment. The performance of the top four models is better for each of the seven major skin issues. The last folder offers a distinct classification method that dynamically incorporates the relevant model into a two-phase detection process utilizing the Targeted Ensemble Machine Classify Model (TEMCM). The final analysis of the model demonstrates improved performance.

Skin cancer is a common kind of malignancy, claims [7]. The disease could be treated if discovered in time. The mortality rate linked with skin cancer is decreased through early identification of malignant lesions using accurate techniques and cutting-edge technologies. Recent AI developments have made it possible to identify skin cancer in medical images. Multi-class classification discrepancy continues to be a problem despite the research and development of various deep learning techniques. This study recommends a mixed approach to categorizing skin conditions. This method combines algorithm-level loss function construction with balanced mini-batch logic and real-time picture augmentation. 24,530 dermoscopic pictures of seven different types of skin disorders make up the training dataset.

Automated segmentation and categorization of skin lesions is the key component of computer-assisted skin cancer diagnosis. Deep learning models are often developed for a single objective, ignoring the benefits of mixing them. For the simultaneous segmentation and classification of skin lesions, researchers advise using MB-DCNN [8]. A coarse segmentation network, a mask-guided classification network, and an advanced segmentation network are all included in this model (enhanced-SN). To help the mask-CN locate and identify skin lesions properly, the coarse-SN offers coarse lesion masks. Use mask-lesion for precise lesion segmentation. The enhanced-SN has been loaded with CN localization mappings. Classification and segmentation networks operate better together by exchanging data. In addition to the Dice loss, researchers create a particular rank loss to address the class imbalance and the hard-easy pixel imbalance. Researchers test the MB-DCNN model on the ISIC-2017 and PH2 datasets and demonstrate that it outperforms state-of-the-art methods for segmenting and classifying skin lesions, with Jaccard indices of 80.4% and 89.4% and average AUCs of 93.8% and 97.8%, respectively. Their results suggest that bootstrapping a unified model may simultaneously enhance segmentation and classification of skin lesions.

Herpes zoster (HZ) is a common skin illness that requires quick diagnosis since persistent pain syndrome might develop if antiviral medication is not administered within 72 hours. AI-powered mobile HZ diagnosis might prevent neuropathy, reduce physician fatigue, and provide financial savings. Mobile device-taken clinical images may exhibit visual artifacts like motion blur and noise that might fool an automated system. The study presented in [9] trains a deep neural network (DNN) to distinguish between HZ and other skin conditions using photos provided by users. In order to increase resilience while lowering computational costs, researchers suggest knowledge distillation from ensemble via curriculum training (KDE-CT), in which a student network learns from a stronger teacher network. A dataset on skin conditions was generated, and contamination was examined for HZ diagnosis. 13 DNNs were evaluated on photographs that were both intact and damaged. The outcomes of the experiment show that KDE-CT improves corruption resistance. With 549 times less multiply-and-accumulate operations, their trained MobileNetV3-Small beat the DNN ensemble, making it suitable for mobile skin lesion analysis.

According to [10], tele-dermatology is a popular telemedicine and e-health application. Specialists in this sector get medical information through telecommunications. Tele-dermatology is a great way to diagnose skin lesions, especially in rural areas. Determine a referral limit for uncompensated clinical treatment and prioritize dermatological patients. Images of skin lesions from several servers are categorized in this research. Modules for classification and localization/segmentation are included in the suggested framework. Researchers provide a hybrid method for the localization module that combines 16-layer convolutional neural network binary pictures with HDCT-based saliency segmentation. To extract the maximum information from binary pictures, a segmented RGB lesion image is produced using a maximal mutual information method. A pre-trained DenseNet201 model is retrained using transfer learning in the classification module. The obtained features from the two completely connected layers are down-sampled using T-SNE. A multi-class ELM (MELM) classifier receives the merged data after these properties have been combined using MCCA. By contrasting their method with innovative techniques, their method's efficiency is shown for different scenarios.

For automated skin lesion segmentation from thermoscopic pictures, work in [11] provides a convolutional neural network (CNN) paired with a particular and effective adaptive dual attention module (ADAM). Three benefits come with the ADAM method. Researchers initially include two global context modelling approaches into ADAM to handle form irregularity, one to capture skin lesion border continuity by global average pooling and the other to address pixel-wise correlation. Their network can extract more detailed and precise skin lesion boundary features thanks to ADAM. Second, the proposed ADAM makes multi-scale resolution fusion achievable, increasing the accuracy of segmentation. Thirdly, compared to conventional CNNs, their method reduces redundancy by giving weight to geographic information. Twin encoders are used in the suggested network to expand the receptive field while maintaining network characteristics. Depending on the extent of the lesion, various ADAMs dilate at varying rates to capture distinctive details. Without employing network ensemble techniques, especially those that include attention processes, their solution outperforms cutting-edge deep learning models in terms of segmentation performance.

An rise in skin temperature is a common sign of vascular problems in the extremities, according to [12]. Differences in blood flow are correlated with variations in skin surface temperature. They proposed that skin temperature would be affected by reduced blood flow in stenotic (subcutaneous) peripheral arteries. One may be able to identify or track the development of vascular diseases, in which subcutaneous blood perfusion plays a crucial role, by detecting temperature gradients across skin surfaces (e.g., peripheral artery disease). This study investigates how the local changes in skin temperature (LST) of healthy individuals (15 males, 30.5.2 years old, and BMI 25.1.2 kg/m2) change in response to two physical challenges intended to alter their hemodynamic state. Four central skin temperatures (head, neck, chest, and left shoulder) and four peripheral skin temperatures (left upper arm, forearm, wrist, and hand) were measured using an infrared thermal camera. Comparability of regional patterns. The core region's temperature hardly altered. Their results suggest that non-contact peripheral temperature fluctuations may be assessed using infrared video data. Peripheral vascular disease patients will have thermographic exams.

A highly contagious pediatric illness called hand, foot, and mouth disease (HFMD) is characterized by fever, diarrhea, oral ulcers, and rashes on the hands, feet, and mouth. This disease's lesion pattern, which has quickly spread over many Asian-Pacific countries, may mirror that of herpangina, aseptic meningitis, and poliomyelitis. Clinical symptoms are necessary in addition to the location and characteristics of the skin lesion to diagnose this condition. Deep learning could make computerized HFMD diagnosis easier. In order to classify and diagnose skin problems, machine learning and deep learning are applied. These models only categorize pictures. The classification of images could misdiagnose skin conditions with similar appearances. Clinical indicators and images may help with illness classification and diagnosis. No deep learning architecture can accurately identify HFMD using just clinical data and photos. According to the study [13], HFMD may be diagnosed using a special hybrid deep neural network architecture that combines clinical and imaging data. The Multi-Layer Perceptron (MLP) network is used in the first branch of the proposed hybrid deep neural network to extract clinical data, while MobileNet or NasNetMobile is used in the second branch to extract features from images of skin disease lesions. The characteristics of both branches are combined using clinical data and images to create an integrated feature for the classification network. Researchers conducted investigations utilizing both clinical and imaging data. They contrasted the conventional MLP and CNN models with their proposed hybrid deep neural network architectures. The proposed method enhances the MLP model for categorization of diseases based on clinical symptoms and picture classification. Cross-validation experiments show that Hybrid Deep Neural Networks are 99–100% accurate in spotting sickness.

Systemic sclerosis (SSc), a rare autoimmune disease, is indicated by fibrosis of the skin and organs [15]. The secret to effective treatment and management is early diagnosis. Deep learning techniques for voice recognition and medical image processing are particularly significant in biology, medicine, healthcare, and biomedical applications. The need for a large training data set and a graphics processing unit (GPU) limits the utility of machine learning methods as diagnostic tools in environments with restricted resources (e.g., clinics). A mobile deep learning network for SSc skin characterisation is provided by researchers. The UNet, a dense connection convolutional neural network (CNN) with additional classifier layers, and a mobile training module make up the recommended network architecture. The network was trained to improve computational efficiency and diagnostic accuracy using MobileNetV2, a highly effective training model for mobile and embedded applications. Researchers classified a different dataset of skin photos using MobileNetV2 as normal, early (mild to moderate) SSc, or late (severe) SSc. On the training, validation, and assessment picture sets, the network worked properly. The CNN had 100% accuracy on the training set, 87.7% accuracy on the validation set, and 82.9% accuracy on the testing set using normal, early, and late phase SSc skin pictures. In comparison to MobileNetV2, CNN is more reliable and effective in identifying images of normal, early, and late phase SSc skin. Conclusions: Their preliminary SSc characterization investigation indicates that the suggested network design has potential. The suggested network architecture offers a quick, affordable, and reliable SSc screening tool that is easily implementable in an effective set of clinical settings.

Machine Learning based Methods for identification of skin diseases

Skin cancer detection depends on the accurate identification and classification of skin lesions [15]. Existing deep learning-based CAD approaches have trouble identifying tough skin lesions with blurry edges, artifacts, low contrast, and small training datasets. They rely heavily on millions of parameters being adjusted properly, which causes overfitting, subpar generalization, and excessive computer resource use. In automated skin cancer diagnosis, this study presents a novel framework for segmenting and categorizing skin lesions. Two phases make up the recommended structure: The complex and diverse properties of skin lesions are initially learned using an encoder-decoder Fully Convolutional Network (FCN), with the encoder learning the lesion's coarse appearance and the decoder learning the borders' subtleties. For effective training and long-term retention, their FCN is made up of sub-networks connected via a variety of long-jump and short-cut links. The Conditional Random Field (CRF) module, which uses pairwise Gaussian kernels for contour refinement and lesion boundary localization, is also part of the network. The second level exhibits an FCN-based DenseNet structure made up of dense blocks connected by concatenation and transition layers. Processing performance is increased and network complexity is decreased by modifying hyper-parameters. This approach encourages feature repetition due to its constrained parameters and data requirements. On the publicly accessible HAM10000 dataset, the suggested model achieved 99% AUC, 98% accuracy, and 98.5% recall.

Numerous research have connected bacteria to human disorders including obesity, liver cancer, and other issues, according to a study published in [16]. Identifying the link between infections and diseases is a crucial component of bioinformatics. A great potential to create computer techniques for forecasting microbe-disease correlations is presented by databases of links between microbes and diseases. By combining disease similarities and current interactions into a heterogeneous network, researchers propose a low-rank matrix completion technique (MCHMDA) for predicting the connections between microbes and diseases. Based on known connections between bacteria and diseases as well as GIP kernel similarity, the microorganism is comparable. Microorganisms are more similar to humans when some parts of their bodies are taken into account. The average of GIP, symptom, and functional similarity is disease similarity. Researchers build a heterogeneous network by combining the networks for illness similarity, microbial similarity, and known microbe-disease associations. By filling up a matrix, SVT calculates the association scores for unidentified microbe-disease pairs. Researchers use 5-fold and Leave-One-Out Cross Validation to examine MCHMDA and other cutting-edge methodologies. Compared to other methods, MCHMDA has a higher AUC on the HMDAD benchmark dataset (AUC). When compared to other methods, MCHMDA offers the highest AUC values in 5CV and LOOCV. Researchers establish the general application of MCHMDA using a larger dataset of microbe-diseases (HMDAD-SUP). Case studies show precise predictive skills.

Optoacoustic (photoacoustic) mesoscopy has been shown to overcome skin challenges encountered during illness detection, diagnosis, and therapy [17]. It is essential to quickly, accurately, and automatically identify the skin surface while doing quantitative analysis on clinical optoacoustic pictures. Most edge- and surface-detection algorithms are unable to reliably identify the skin surface in RSOM pictures because of discontinuities and fuzzy interfaces. Researchers provide a dynamic programming (DP) method that extracts the skin border as a 2D surface in a single step rather than using several 1D outlines. A domain-specific energy function is presented using the volumetric optoacoustic mesoscopy picture properties. The efficacy of the suggested method is validated using volar forearm scans of 19 individuals with different skin tones for whom the skin surface was manually specified. Low contrast or ill-defined skin borders reveal the limitations and resiliency of the strategy. Clinical translations and RSOM photos are processed more quickly and accurately thanks to automatic skin surface recognition. Their method may be used to recognize different RSOM surfaces and imaging techniques.

Skin problems have biological similarities, according to a number of clinical studies [18]. These similarities make it challenging to identify skin cancer and spur the creation of cutting-edge clinical decision support systems. In a single test, gene expression analysis may find DEGs that signify a variety of skin conditions. The right pipeline architecture is required for a variety of varied transcriptome datasets, including batch merging, biomarker detection, and automated classification assessment. This article employs a cutting-edge strategy to address these technological difficulties in order to provide novel viewpoints on skin cancer diagnosis. Using a panel of eight multiclass DEGs, their investigation discovered a panel of eight skin pathological states that could be distinguished, including two precancerous skin illnesses, two cancerous skin problems, and six healthy skin conditions. The recognition of new samples was used to rate classification models. The overall and average F1-scores were higher than the corresponding recognition rates of 94% and 80%. Clinicians should look at how skin problems and multiclass DEGs with large gene expression abnormalities are related at the molecular level.

According to [19], accurate skin lesion classification is challenging because to the similarity across classes and variance within classes of skin lesion pictures, as well as the poor generalizability of a single Deep Convolutional Neural Network trained with limited data. Researchers develop a model called the Global-Part Convolutional Neural Network (GP-CNN) that treats local and global inputs equally. In the Global-Part paradigm, a G-CNN and a P-CNN are combined (P-CNN). In order to create the Classification Activation Map, G-CNN is trained using downscaled dermoscopy pictures to extract information at the global level (CAM). During P-CNN training, data on localized skin lesions are collected using CAM-guided image patches. Additionally, researchers provide a data-transformed ensemble learning approach that, by combining discriminant data from GP-CNNs trained with the original, color constancy, and feature saliency changed pictures, may enhance classification performance. Using Skin Lesion Challenge (SLC) datasets from 2016 and 2017, the proposed method is evaluated. According to AP values of 0.718 for the ISIC 2016 SLC dataset and an Average Auc value of 0.926 for the ISIC 2017 SLC dataset, the suggested technique may be able to classify skin lesions at the state-of-the-art level without the need of outside data.

Melanoma is caused by UV light from the sun, and it has a 15-20% survival rate, according to [20]. Melanoma is a severe cancer that may spread to the liver, lungs, and brain if it is discovered too late. Doctors compare pigmented skin lesions to detect melanoma. The performance of biopsies as a consequence of inaccurate analysis hampers treatment. The melanoma diagnostic process may be sped up by computer vision by independently analyzing dermoscopy pictures. These treatments are ineffective, as seen by the apparent similarities between healthy and diseased skin, gel bubbles, hair, and clinical markers. The methods used in this study for segmenting and detecting melanoma is an improvement over the previous approach. Dermoscopy pictures are first cleaned up using morphological approaches to get rid of hairs, gel bubbles, and clinical marks.

To pinpoint sick areas, researchers modified the YOLOv4 object detector to find melanoma. The afflicted regions are retrieved using active contour segmentation once the melanoma boundary boxes have been constructed. The effectiveness of state-of-the-art melanoma detection and segmentation methods is evaluated and compared using the ISIC2018 and ISIC2016 datasets. Their technique yields an average die score of 1 and a Jaccard coefficient of 0.989. Their plan to create a clinical decision support system for melanoma diagnosis is supported by the segmentation findings. On the same person, the YOLOv4 detector may detect a variety of skin conditions.

A low-cost near-field probe for the early detection of skin cancer is described in work in [21]. The device's tapered form concentrates the electric field at its tip. Fabrication is simple and economical when SIW technology is used. Direct skin contact is made possible by the probe's high dielectric constant substrate, which matches the impedance of the skin. With this capacity, a variety of skin locations may be quickly scanned using the suggested technique. Without endangering the nearby biological tissues, the probe uses 40 GHz to locate and identify small skin cancer tumors. The detection depth, a more accurate measurement than penetration depth, describes the farthest distance a tumour may be detected from the skin's surface. The probe can work on any kind of skin and every part of the body thanks to the differential imaging algorithm. The proposed device has a lateral sensitivity of 0.2 mm and a detection depth of 0.55 mm. The probe was designed, modeled, created, and tested using a phantom with synthetic human skin.

Using photographs of skin lesions as its basis, deep neural network-based computer-assisted skin cancer classification systems are said to give recommendations [22]. Despite successful results, patient traits may enhance the efficiency of skin lesion screening. Researchers identify skin cancer by combining images and data sources using deep learning algorithms. A cutting-edge technique called Metadata Processing Block (MetaBlock) uses metadata to enhance the most crucial aspects of a picture and aid in data classification. The proposed method was contrasted with MetaNet and feature concatenation. In six out of ten scenarios, their method performs better than previous combination strategies, and it improves classification for all tested models.

Breast cancer may cause significant and measurable skin changes because of the interstitial matrix and lymph system, according to [23]. This study assessed the potential use of variations in skin electrical resistance as a diagnostic and treatment biomarker for benign and malignant breast cancer lesions. 48 ladies took part in this study. During the same session and a week later, skin resistance measurements were taken in the breast lymphatic area and non-breast lymphatic regions. Repeatability was assessed for both intrasession and intersession using intraclass correlation coefficients. The data were altered in order to evaluate the cross-sectional differences between benign disease and breast cancer. Six people who received therapy were assessed using longitudinal data throughout the course of six months. Comparing differences in ratio metrics across groups may be done using descriptive statistics. A dep forest (DF) classification system was trained to recognize breast cancer lesions using skin resistance data. Before and after treatment, there were notable differences between malignant and benign breast lesions (p0.01). To improve their method and look more closely at the biophysical changes, further research is required.

Early cancer identification (stage I) increases patient longevity and lowers treatment costs, according to a research published in [24]. Millimetre-wave radars may be able to detect skin tumors based on their electrical properties. According to this study, skin cancer may be detected using a low-power multitone continuous-wave radar operating at 77GHz. A low-cost MHMIC architecture is used in the sensor. A ceramic substrate measuring 0.127 mm was used to mount the sensor. Modules for the transmitter and receiver employ arrays of patch antennas with 16 elements. homodyne quadrature down-converter with six ports. Employing HSCH-9161 It is possible to make combined power detectors and Schottky diodes. The metal sensor was 35 x 45 mm in size. Each power detector's output baseband voltages are amplified by two cascaded amplifier circuits. The proposed radar is able to identify the dielectric properties of tissues, making it suitable for the precise micron-level detection of melanomas.

According to research from [25], early detection of skin cancer increases the five-year survival rate. Even skilled dermatologists are unable to identify malignant skin tumors in their early stages. Other methods for identifying dermatoscopic pictures do exist, but they are labor-intensive and inefficient at detecting skin cancer. For the classification of dermoscopic pictures in this article, FixCaps is recommended. FixCaps has a larger receptive field than CapsNets since its bottom convolution kernel is 3131 rather than 99. The loss of spatial information caused by convolution and pooling was reduced using the convolutional block attention module. To avoid the capsule layer model being underfit, group convolution was utilized. In comparison to traditional methods, the network reduces calculations while increasing detection accuracy. FixCaps outperforms IRv2-SA, which has a skin cancer diagnosis accuracy of 96.49% on the HAM10000 datasets.

Due to background noise and lesion complexity, automated dermoscopy lesion detection is challenging [26]. To increase detection accuracy in previous methods, larger and more intricate models were used, but little is known about how lesion features vary within and across classes. Algorithm application to larger models is substantially more challenging. It was recommended to use a simple method with fine-grained classification for skin cancer diagnosis. Lesion categorization and feature discrimination networks are included in the suggested model. The feature extraction module of the recognition model receives initial positive and negative training examples (Lightweight CNN or LCNN). The suggested recognition approach could extract more discriminative lesion characteristics with fewer model parameters and enhance the model's performance in terms of recognition. The suggested method outperforms the state-of-the-art deep learning-based strategy on the ISBI 2016 skin lesion analysis towards melanoma diagnosis challenge dataset. Based on the proposed recognition model's feature extraction module, U-Net architecture, and migration training strategy, researchers create a lightweight semantic segmentation model of the dermoscopy lesion area that can achieve good end-to-end segmentation accuracy without expensive image pre-processing operations.

[27] asserts that earlier detection of skin cancer, particularly melanomas, enables more successful treatment. Due to the rise in skin cancers, a computerized analysis of skin lesions is required. There aren't many ground truth segmentation labels in the datasets for skin lesions that are presently accessible. The segmentation datasets presently available incorporate imperfect expert annotations since precise annotations to determine the boundaries of skin lesions take time and money. For correctly recognizing lesions in dermoscopy pictures and diagnosing skin lesions, lesion border segmentation is essential. To segment lesion margins, researchers provide fully automated deep learning ensemble techniques. The Mask R-CNN and DeeplabV3+ ensemble algorithms were trained using the ISIC-2017 segmentation training set, and their performance was assessed using the ISIC-2017 testing set and PH2 dataset.

According to [28], melanoma is the most serious kind of skin cancer. Worldwide, melanoma has a greater mortality rate than other malignancies. Melanomas may be recognized using a variety of computer-assisted techniques. Designing an efficient CAD system for melanoma detection is challenging due of the nevus' poor optical appearance. Existing methods either employ traditional machine learning models with pre-selected features or deep learning-based techniques utilizing full pictures. Research on automatic and discriminative feature extraction for skin cancer may enhance deep learning instruction. The lack of visuals hinders deep learning algorithms as well. Researchers suggest building a Region of Interest (ROI)-based technique for separating melanoma from nevus malignancy using transfer learning. An enhanced k-mean approach is used to extract ROI from photos. Using photos of just melanoma cells, this technique trains the computer to recognize distinctive features. Researchers apply a CNN-based transfer learning (CNN TL) model with data augmentation for ROI images from DermIS and DermQuest. DermIS and DermQuest both have accuracy rates of 97.9% and 97.4%, respectively. ROI-based transfer learning outperforms traditional picture classification systems.

Skin cancer is brought on by aberrant cell proliferation, claims [29]. If found early, melanoma and focal cell carcinoma may be avoided. Early skin cancer detection and classification are expensive and challenging. ConvNets and recurrent networks are two examples of deep learning architectures designed for automatically extracting challenging features. In order to enhance the performance of ConvNet models, this research suggests a cascaded ensembled network that combines a ConvNet model with a unique multi-layer perceptron. This method retrieves non-manufactured visual data including color moments and texture qualities using a convolutional neural network. The combined deep learning model's accuracy is 98.3%, compared to a convolutional neural network's accuracy of 85.3%.

Skin cancer has been detected using a number of modern neural network topologies with overparameterized regimes [30]. A recent study found that networks with polynomially fewer hidden units outperform models with excessive parameters. Researchers describe a multistage unit-wise dense residual network with transition and additional supervision blocks that encourages shorter connections for improved feature representation. Researchers constructed the network differently from ResNet, with densely coupled residual units in several stages, to enhance residual learning and limit skip connections. For greater performance levels, each layer may believe that its previous levels were more basic than the local network of its rivals.

Low complexity models for identification of skin diseases

[31] claims that one of the worst forms of cancer is skin cancer. Compared to unaided eye examination, image analysis enhances automated identification of malignant melanoma and other pigmented skin diseases. However, because to their limited scalability, Deep Neural Networks (DNN) are not ideal for the construction of large-scale models. Deep Neural Networks (DNN) are a common method for automating the identification of skin abnormalities. This study uses transfer learning to categorize skin lesions using labelled data from a different domain (source). In order to represent discriminative information from several picture views with an equitable weighting approach, it proposes a multi-view filtered transfer learning network. Additionally, each source picture is assessed for relevance using this method, which extracts positive information while discarding unfavorable information. Their technology can successfully and scalable detect Seborrheic Keratosis and Melanoma, according to rigorous skin lesion categorization tests. The advantages of the multi-view filtered transfer learning approach that researchers promote are further shown by the explanation of the major elements.

[32] claims that skin cancer is the most common kind of cancer and that it is more treatable at an early stage. Dermatologists divided the skin lesion area into sections for planning. Segmentation is necessary for efficient treatment. In recent years, deep convolutional neural networks have been proposed as segmentation techniques. Encoding and decoding blocks are used in common segmentation algorithms (like U-Net) to specify local and semantic representations. These constructs must significantly change both their shape and texture in order to accurately mimic multiscale things. It is advised to use Multi-Scale Attention U-Net for segmenting skin lesions (MSAU-Net). The traditional U-net is improved by adding an attention mechanism at the bottleneck to imitate hierarchy. Through nonlinear aggregation, the attention module alters the multi-level representation's representational characteristics. Then, it recovers often occurring discriminative characteristics and suppresses less useful ones using a BDC-LSTM structure.

Skin cancer is caused by abnormal cell proliferation, according to a research published in [33]. Rapid cell division eliminates healthy skin cells. An early intervention might reduce mortality. The method for early skin lesion diagnosis, segmentation, and classification is suggested in this article. There are three steps in the process. Using the tinyYOLOv2 model with squeeze Net and an open neural network, phase I includes localizing skin lesions (ONNX). The features of SqueezeNet depthconcat7 are available on TinyYOLOv2. Skin injury is recognized using the suggested model. Using a 13-layer 3D-semantic model, Segmentation Phase II is performed (01 input, 04 convolutional, 03 batch-normalization, and 03 ReLU, softmax and pixel classification).

To identify picture overlap in the segmentation model offered, pixel classification layer is used. Utilize ResNet-18 to extract deep features in Phase III, and ACO to choose the top features. The vector of optimized features is used by classifiers like optimized (O)-SVM and ONB. The proposed method is evaluated using challenging MICCAI ISIC datasets from 2017-2018-2019. Using the described method, early cutaneous lesions were identified, divided, and categorized.

According to [34], melanoma is one of the most deadly types of skin cancer. Early melanoma detection is challenging because of color alterations in similar tumors. Segmentation of skin lesions must be carried out automatically in order to categorize skin diseases. Skin lesion segmentation is improved using deep learning. A possible cutting-edge model is U-Net deep CNN. The majority of deep CNNs, including U-Net, separate skin lesions using a single RGB color picture. For transmitting the chromatic information of skin lesions, the RGB color space is not ideal. The color space that is chosen has an impact on segmentation performance. It is advised to use a single input color u-net, dual input color u-net, or triple input color u-net (TICU-Net). In SICU-Net, DICU-Net, and TICU-Net, a single decoder route connects single, dual, and triple encoder sub-networks. An individual picture color space is given for each encoder sub-network. To create a segmented image map, a channel-wise attention module merges the learned feature maps from each encoder sub-network. The performance of CU-Net models is enhanced by a composite loss function. Three freely available reference datasets—PH2, ISIC 2017, and ISIC 2018—are used to test the recommended models. The experimental results show that the recommended models are state-of-the-art and outperform the original U-Net model.

[35] reports an increase in skin cancer cases all across the globe. Early detection and intervention improve patient survival. The borders of skin lesions must be divided in order to locate lesions in dermatoscopic pictures. Accurate segmentation of cutaneous lesions is challenging due to blurred boundaries, necessitating an automated method. The CSARM-CNN (Channel & Spatial Attention Residual Module) model may be used to successfully separate skin lesions automatically. Each CSARM block creates a new attention module by combining channel and spatial attention. Multiple-scale input pictures are generated using a technique called spatial pyramid pooling. The loss of the model is added to both sides of the output layer using a weighted cross-entropy loss function. ISIC 2017 and PH2 datasets were analyzed, and the results showed 94.96% and 95.23 percent accuracy and 99.03% and 99.45% specificity, respectively.

[36] asserts that skin lesions may be brought on by allergies, infections, sun exposure, etc. Image classification is required for an appropriate diagnosis since a lot of skin illnesses seem to be similar. Since it causes the majority of skin cancer fatalities, melanoma is well-known. To categorize skin lesions, researchers combine test-time regularly spaced shifts with Upgraded Convolutional Neural Networks (UCNN). The shifting method modifies the displacement vectors on a regular lattice to produce multiple duplicates of the test input picture. Ensemble classifiers are given these updated test pictures.

Computer-assisted diagnostics has made significant advancements in the identification of skin lesions using deep learning frameworks, but does not reveal the architecture. Researchers provide a DL-based IVF framework for identifying skin lesions in the publication cited by [37]. The proposed IVF-DL network extracts significant information from dermoscopic pictures using a ResNet architecture. The purpose of this article is to classify skin lesions and provide clear results for each subsequent block. For optimum performance, three method hyperparameters were modified. The spatial characteristics of the final interpretable output were examined using IVG. Experimental results show that the proposed system outperforms existing classification algorithms using four performance measures (accuracy, sensitivity, specificity, and area under the receiver operating curve) and two benchmark datasets.

Melanoma is a serious and increasingly common kind of skin cancer, according to [38]. The most accurate way of diagnosis is histopathology. This study uses decision-level fusion and Hidden Markov Model (HMM) parameters to create a melanoma detection system. Asymmetric analysis is a method for determining how heterogeneous a sample is. Describe an EM-trained HMM classifier based on fusion. A new texture feature is produced using the microscopic image's statistical histogram characteristics and local difference pattern (LDP). The suggested technique for melanoma detection has an error rate of 0.04%, according to extensive testing.

[39] developed an innovative method for differentiating between 10 different types of skin lesions using Fourier spectral data in an additive color model. An ANN receives all spectral information as well as correlation coefficients between different kinds of skin lesions. Despite the presence of strange objects, poor clarity, and black sections in some of the analyzed images, the results show accurate classification for all classes of skin lesions based on high Accuracy, Precision, Sensitivity, and Specificity metrics performance and a reduced percentage of misclassified images (5.9%) for the Testing sub-dataset and even less for the Training (2.8%) and Validation (5.6%) sub-datasets. The three tumors with the highest ROCs are basal cell carcinoma, seborrheic keratosis, and melanocytic nevus, whereas Pyogenic Granuloma has the lowest ROCs.

Low delay models for identification of skin diseases

Melanoma is a lethal kind of skin cancer, claims [40]. Due to a lack of annotated skin lesion pictures and intraclass unbalanced datasets, classifying skin lesions using deep learning is challenging. Practitioners must use data augmentation techniques based on GANs to identify skin lesions and provide more precise diagnosis. When deep learning is applied for medical diagnosis, insufficient sample sizes may have an impact on the classification accuracy of skin lesions. This study proposes a brand-new categorization system for skin lesions based on the patterns of enhancement of skin lesions (SLA-StyleGAN). To create high-quality photographs of skin lesions, the recommended framework reconstructs the discriminator and redesigns the style control and noise input of the original generator. Researchers provide a unique loss function that reduces intraclass sample distance while increases interclass sample distance in order to increase multiclass accuracy (BMA). The recommended method helps the diagnosis of diverse skin lesions, improves the classification of skin lesion images, and analyzes skin lesions at various stages, including those that are difficult to detect.

The prevalence of skin cancer is increasing worldwide as a result of a lack of information among the general population and skin specialists [41]. Skin cancer may be detected and diagnosed at an early stage thanks to medical imaging. Medical professionals often employ manual diagnosis, however its accuracy may be limited by unskilled dermatologists. The automated system must assist doctors in the early diagnosis of skin cancer in order to prevent death. In this research, a hybrid feature set and machine learning are used to automatically identify skin lesions. Deep properties of AlexNet may be used to precisely predict skin lesions. The proposed model is tested using melanoma and nevus images from two publically accessible datasets. The usefulness of machine learning with heterogeneous characteristics is shown by both datasets. The suggested model's ensemble classifier has a 94.7 percent accuracy rate.

[42] asserts that the heterogeneity within and across classes makes it challenging to diagnose skin cancer using dermoscopy pictures. Despite the fact that the majority of these algorithms extract characteristics from high-resolution global pictures, deep convolutional neural networks (CNNs) have attracted attention for automated skin cancer diagnosis. These techniques result in information loss while lowering the size of provided photos. The lack of dermoscopy images is another issue. Researchers provide a method that uses patch-based local deep feature extraction to improve classification accuracy. The recommended method integrates features from many areas of a dermoscopy image to maintain fine details. A feed-forward neural network is used to detect skin cancer, while kernel PCA is used to identify significant characteristics. Experiments have shown that the suggested approach is better to the established ones. Additionally, pre-trained CNN models are compared.

In skin lesions, dermoscopy [43] may be used to find telangiectasia. When basal cell carcinoma develows, telangiectasia occurs. These vessels divide into smaller vessels because they are arborizing, thready, and serpiginous. There aren't any simple or automatic procedures to recognize them. In this study, U-Net is used to automatically segment dermoscopic pictures for telangiectasia. Our ability to recognize telangiectasia on digital pictures of basal cell carcinoma is made possible by combining image processing and deep learning. Researchers look at loss approaches and apply a hybrid loss function to boost performance in order to overcome the difference in pixel class between skin and blood vessels. A pixel-based method (PB) is created by researchers to identify telangiectasia in skin cancer photos. Analyses of the variation in human observers' annotations are conducted.

For the correct diagnosis of skin cancer and melanoma, skin lesion detection and classification (SLDC) is required. Dermatologists may find decision-making and case assessment using AI and image processing technologies helpful. Because there are so many filters and layers, all deep learning (DL) designs take more time to complete. It must be retrained if the architecture is insufficient to prototype the classification system. Dermoscopic skin lesions may be classified using a broad learning system (BLS) that uses an incremental learning algorithm, according to the research reported in [44]. BLSNet is the proposed model. BLSNet-based SLDC models beat DL-based SLDC models with 99.09% accuracy and 98.73% F1-score, according to experiments on the ISIC 2019 and PH2 datasets. BLSNet executes in 0.93 seconds, which is quicker than conventional methods.

Environmental factors such extreme heat, dust, smoke, and sun may contribute to a variety of illnesses, especially dermatological ones, according to a research published in [45]. Dehydration, dirt, bacteria, low nourishment, and other factors may induce eczema, while delivery or harsh sunlight can produce harmful moles. It is essential to detect skin illnesses right away, particularly eczema and hazardous moles, and to build a less costly diagnostic approach with the help of specialists in order to prevent disease aggravation due to environmental, physiological, and chemical factors. Eczema and other skin conditions will be difficult to treat if they become worse. This study aims to obtain a picture of the infection location and evaluate it to help medics. In this study, clinical imaging data and a decision tree methodology were used to classify illnesses. Along with the fundamental idea, it is correctly determined. evaluating the results of the current decision-tree assisted image processing and classification method. Decision trees are more sensitive, accurate, and selective than image processing. When decision tree (CDT) and image processing methods are at odds, the application alerts users. In such case, heed the doctor's advice. The technology from this study may be used to detect harmful moles and eczema in order to improve and protect human life. For this examination, samples of the body's layers were taken. Normal conditions alter the meaning. This method aids in the identification of eczema and cancerous moles. Additionally, healthy skin is involved. This study summarizes the typical state in an effort to help medical professionals.

According to study in [46], melanoma is one of the most lethal kinds of cancer. Melanocytic cells are considered to multiply uncontrolled. Disease diagnosis is now carried out using deep learning and machine learning algorithms. Images and dermatological scans are two types of visual data that are used in melanoma research. This necessitates a melanoma detection tool that is more accurate. In this research, neural networks are used to achieve the same result. Researchers suggest a CNN framework-based deep learning model to improve melanoma detection. This model adjusts the input array size, activation functions, and network design. High melanoma detection accuracy was shown using Resnet, DenseNet, Inception, and VGG. Most of the information was categorized as benign or malignant. Melanocytic nevi, melanoma, benign keratoses, basal cell carcinoma, actinic keratoses, vascular lesions, and dermatofibroma are a few of the lesions included in their database. Researchers altered the accuracy and input quality using deep learning methods and the HAM10000 dataset. Positive results show that it is reliable.

[47] claims that skin cancer is a growing worldwide health problem. It is challenging to create an image-based

benign-malignant classification system due to the subtle distinctions between benign and malignant skin lesions' appearances. In this study, a computer-aided design (CAD) technique is presented for accurately and efficiently classifying skin lesions with little computational complexity. It is possible to get rid of hair and artifacts using morphological filtering. Grab-cut automatically and with minimal assistance from humans segments HSV skin lesions. Current research focuses on automated ABCD rule execution for image processing algorithms to distinguish malignant melanoma from benign lesions. The VGG-16, ResNet50, ResNetX, InceptionV3, and MobileNet are used to classify benign and malignant skin lesions. The best 5-fold cross validation outcomes are obtained when SVM and the ResNet50 architecture are combined. The results show that, in contrast to using fresh photos, data augmentation enhances training and testing performance. The proposed diagnostic framework surpasses current contemporary approaches when used to diagnose actual clinical skin lesions in terms of area under the ROC curve (99.52%), accuracy (99.87%), sensitivity (98.87%), precision (98.77%), F1-score (97.82), and time (3.2 s). The recommended method could help doctors categorize skin lesions.

Skin cancer is one of the most prevalent human illnesses that may be seen [48]. Given the significance of early skin cancer diagnosis, creating an automated categorization system for skin lesions is difficult when designing digital medical systems. The use of CNN models for automated dermoscopy-based melanoma diagnosis is more common than ever. Dermoscopy is used in this study to detect skin cancer at an early stage. The CNN VGG-16 network architecture is used in the model. The suggested framework builds a skin cancer detection model utilizing a modernized VGG-16 architecture. Researchers compared the new strategy to current methods while evaluating the dataset from the International Skin Image Collaboration. In terms of accuracy, the suggested model outperforms the alternatives.

Skin cancer is a common worry, according to study [49]. The cancer that is now most common is melanoma. Having this kind of skin cancer is risky. The easiest way to solve the issue is to raise awareness and identify it early. Machine learning-based skin cancer detection is necessary to save lives quickly. CNNs are used by researchers in their methodology for identifying skin cancer. The suggested technique promptly detects skin cancer.

[50] claims that skin cancer (SC) is the world's worst disease, taking millions of lives each year. In order to identify any SC signs or symptoms and improve a patient's chance of survival by 70%, frequent head-to-toe skin exams are advised. SC diseases may be categorized and identified using ML-based methods. Correctly diagnosing these illnesses is hampered by lower detection accuracy, limited model generalizability, and a paucity of labelled training data. A two-tier SC classification system was developed for this project. In the beginning, researchers increased the number of training picture samples by using data augmentation. An MVT-based classification model for SC was developed by researchers and placed in the second layer of the architecture. Similar to word embedding, this MVT transmits picture patches to the transformer by dividing the input image into image patches. The input picture is classified using Multi-Layer Perceptron (MLP). Researchers found that the proposed MVT-based model outperforms existing cutting-edge SC classification techniques on the Human against Machine (HAM10000) datasets. Thus, it can be shown that the internal functioning properties of the present models vary greatly. The next section analyzes various models based on their levels of accuracy, latency, computing complexity, scalability, and deployment cost in order to assess them in terms of their quantitative performance. This will help readers choose the best models for their use cases, depending on performance levels.

STATISTICAL ANALYSIS AND COMPARISON

Following a comprehensive assessment of the current models for the diagnosis of skin diseases, it has been shown that these models exhibit a great deal of diversity in terms of their intrinsic properties. Therefore, as a result of the extensive theoretical research that was done on models for detecting skin cancer, it has come to light that current models exhibit a great deal of diversity with regard to the functional properties that they exhibit. This was discovered as a result of the fact that current models were subjected to extensive research. Because of this, it might be difficult for researchers to choose the most appropriate models for the application-specific performance use cases that they are working on. This section offers a discussion of an empirical study of the streaming models that have been examined in terms of accuracy of classification, computational complexity, delay required for classification, scalability, and cost of deployment when applied to real-time settings. This section's objective is to make this work easier for readers by providing assistance in selecting the models that are most suitable for the deployment needs that they have. Although the degrees of accuracy were presented in the study papers in a plain and accessible format, other characteristics were not assessed in terms of their absolute value metrics. As a consequence of this, the measurements of these parameters were quantized into fuzzy levels consisting of Low (L=1), Medium (M=2), High (H=3), and Very High (VH=4) ranges. These ranges were determined based on the characteristics of the internal implementation of these parameters. For instance, CNNs call for a higher degree of complexity than linear classification models; hence, the complexity levels of CNNs will be higher; this will assist readers in evaluating which models are optimal based on their specific metric sets. When seen through the lens of this methodology, the findings of the empirical inquiry into these metrics are shown in table 1 as follows:

Table 1. Pragmatic evaluation of different skin disease detection models based on empirical parametric sets

Method	Accuracy of Classification **(%)**	Cost of Deployment	Computational Complexity	Delay required for Classification	Scalability	Reference
CNN TSP TL	98.5	H	VH	M	H	1
SPBL	90.2	H	H	M	H	2
DCNN	96.4	VH	H	H	H	3
DRANet	99.5	VH	H	VH	VH	4
IResNet	94.3	VH	H	H	VH	5
TEMCM CNN	98.1	VH	H	H	H	6
Deep CNN	95.4	VH	H	M	VH	7
MB DCNN	96.2	VH	VH	H	H	8
DNN	94.3	H	H	H	H	9
MELM	85.5	H	M	H	H	10
CNN ADAM	97.2	H	H	VH	VH	11
LST	91.4	H	M	M	H	12
Nas Net	96.5	H	H	H	VH	13
UNet	98.6	VH	H	M	H	14
CRF	83.3	H	H	M	H	15
MCH MDA	91.4	H	H	H	VH	16
DP	72.5	VH	VH	M	H	17
DEG	90.8	H	H	H	H	18
GP CNN	96.7	VH	H	H	H	19
YOLOv4	99.4	M	M	L	VH	20
SIW	94.2	H	H	M	M	21
MetaNet	97.3	VH	VH	H	H	22

DF	91.6	H	M	L	VH	23
MHMIC	90.8	H	H	H	H	24
CapsNets	99.2	VH	VH	H	H	25
LCNN	97.5	H	M	M	M	26
Mask RCNN	99.1	H	VH	H	H	27
CNN TL	98.4	H	H	M	H	28
Conv Nets	95.9	H	VH	H	VH	29
ResNet	94.7	VH	H	H	VH	30
DNN	99.3	H	H	H	VH	31
MSAU-Net	99.7	VH	H	M	H	32
YoLO ONNX	98.8	VH	VH	H	H	33
TICU-Net	98.2	H	H	H	H	34
CSARM-CNN	99.5	VH	H	VH	H	35
UCNN	94.4	H	H	H	M	36
ResNet DL	95.6	H	H	VH	VH	37
HMM LDP	93.2	H	VH	H	VH	38
ANN	90.8	M	M	L	M	39
SLA Style GAN	99.6	VH	H	VH	H	40
Alex Net	97.1	H	VH	H	H	41
PCA CNN	98.4	H	VH	M	H	42
PB	90.1	H	H	H	H	43
BLSNet	99.2	VH	VH	H	VH	44
CDT	91.4	H	VH	M	H	45
ResNet with DenseNet	97.9	VH	VH	VH	H	46
ResNetX	98.5	VH	H	H	VH	47
VGG-16	96.5	H	H	M	H	48
CNN	96.1	H	M	M	H	49
MLP	94.8	M	H	L	M	50

Based on this analysis, it can be observed that MSAU-Net [32], SLA Style GAN [40], DRANet [4], CSARM-CNN [35], YOLOv4 [20], DNN [31], CapsNets [25], BLSNet [44], and Mask RCNN [27] showcase high accuracy, thus can be used for scenarios where accuracy aware skin disease classification is needed to be deployed for clinical deployments.

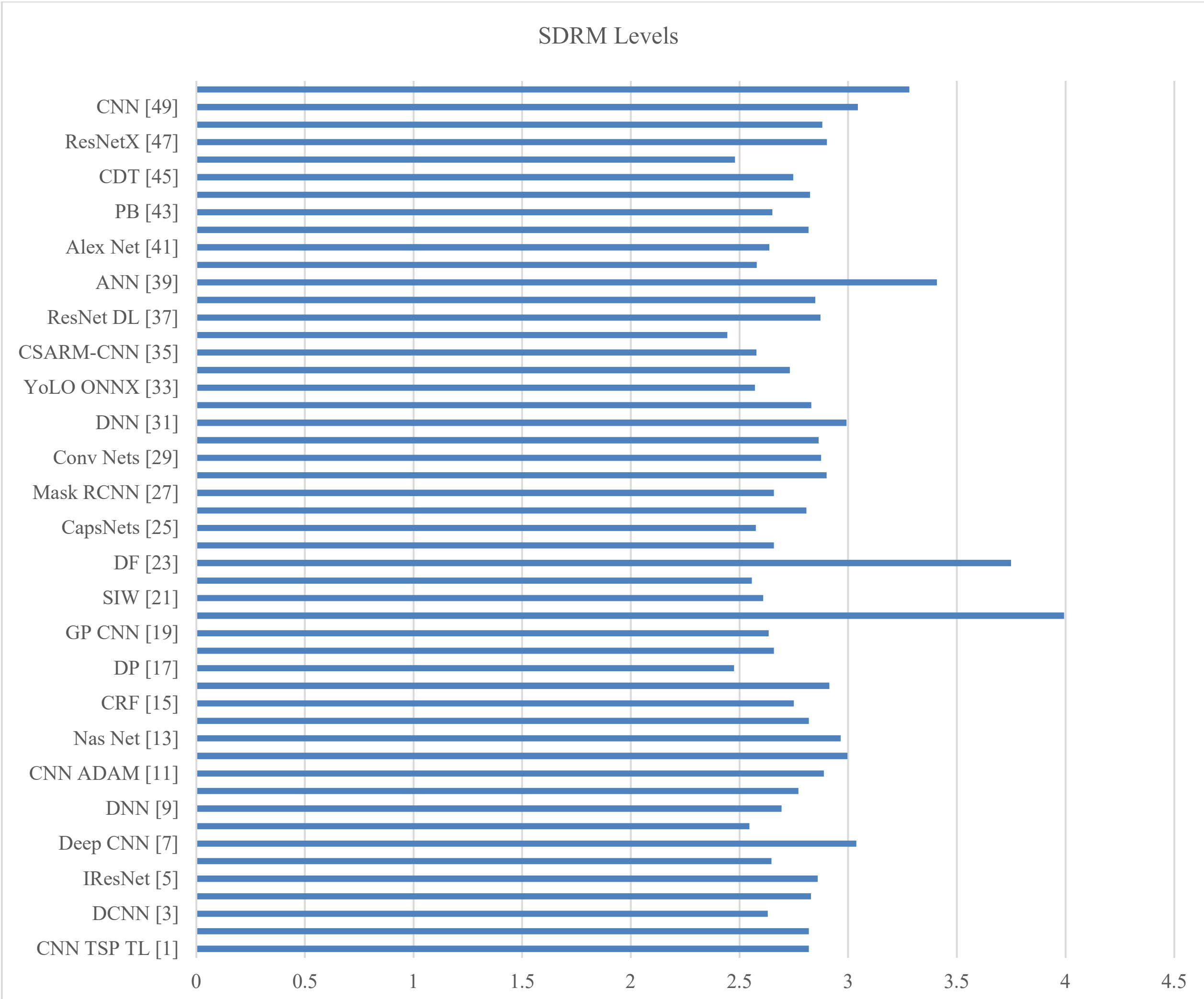

Figure 2. SDRM Performance for different models used to classify skin diseases

This is because, these models use deep learning components that are feature friendly, and thus can be used for multiple scenarios.

It was also observed that YOLOv4 [20], ANN [39], and MLP [50] are able to achieve low cost, thus can be used for cost-aware use cases. The reason for this low cost is the use of simplified components while designing classifier models.

While, it was analyzed that MELM [10], LST [12], YOLOv4 [20], DF [23], LCNN [26], ANN [39], and CNN [49] showcased low complexity, thus can be used for high-speed clinical applications. This is due to use of low error and low complexity modules, which minimizes delay during classification operations. In terms of delay, YOLOv4 [20], DF [23], ANN [39], and MLP [50] are capable of achieving better performance, which is due to integration of high-speed modules, but it causes them to reduce accuracy levels.

It was observed that DRANet [4], IResNet [5], Deep CNN [7], CNN ADAM [11], Nas Net [13], MCH MDA

[16], YOLOv4 [20], DF [23], Conv Nets [29], ResNet [30], DNN [31], ResNet DL [37], HMM LDP [38], BLSNet [44], and ResNetX [47] showcase higher scalability, thus can be used for a wide variety of clinical applications. This is because these models use generic components that can be interfaced with existing classification deployments.

Thus, researchers can identify performance-specific models for their deployments. To further simplify this process of selection, a Skin Detection Rank Metric (SDRM) is evaluated, and it combines these comparison metrics via equation 1 as follows,

$$SDRM = \frac{\text{Accuracy of Classification}}{100} + \frac{1}{\text{Cost of Deployment}} + \frac{1}{\text{Computational Complexity}} + \frac{1}{\text{Delay required for Classification}} + \frac{\text{Scalability}}{4} \quad \ldots..(1)$$

Based on this evaluation, and figure 2, it can be observed that YOLOv4 [20], DF [23], ANN [39], MLP [50], CNN [49], Deep CNN [7], LST [12], DNN [31], Nas Net [13], MCH MDA [16], ResNetX [47], and CNN TL [28] showcase low cost, low complexity, low delay, high accuracy and high scalability, thus they must be used for high-performance skin disease detection scenarios. Thus, researchers must use these models for high-efficiency skin disease classification use cases.

CONCLUSION AND FUTURE SCOPE

This text compares and evaluates different deep learning & machine learning models for identification of skin diseases. These models utilize some or the other form of deep feature extraction models along with high accuracy fully connected layers in order to improve classification performance for different skin disease types. Based on this review, it was observed that MSAU-Net, SLA Style GAN, DRANet, CSARM-CNN, YOLOv, DNN, CapsNets, BLSNet, and Mask RCNN have been shown to have a high level of accuracy, and as a result, they are candidates for use in scenarios in which accuracy aware skin disease classification must be deployed for clinical deployments. This is due to the fact that these models make use of deep learning components that are friendly to features and can therefore be applied to a variety of contexts. It was also found that YOLOv, ANN, and MLP are all capable of achieving a low cost, and as a result, they can be used for use cases that are cost-aware. The utilization of simplified components throughout the design process of classifier models is the primary contributor to this cost-effectiveness. While it was determined that MELM, LST, YOLOv, DF, LCNN, ANN, and CNN exhibited low complexity and could therefore be utilized for high-speed clinical applications, it was also determined that these models were analyzed. This is because of the utilization of modules with low error rates and low complexity, which significantly reduces the amount of time spent waiting during classification processes. As a result of the integration of high-speed modules, YOLOv, DF, ANN, and MLP are able to achieve better performance in terms of delay. While this allows them to achieve better performance, it also causes them to achieve lower accuracy levels. It was discovered that DRANet, IResNet, Deep CNN, CNN ADAM, Nas Net, MCH MDA, YOLOv, DF, Conv Nets, ResNet, DNN, ResNet DL, HMM LDP, BLSNet, and ResNetX have higher scalability, and therefore can be used for a This is due to the fact that these models make use of generic components, which are able to be interfaced with already existing classification deployments. When these metric evaluations were combined, it was discovered that YOLOv, DF, ANN, MLP, CNN, Deep CNN, LST, DNN, Nas Net, MCH MDA, ResNetX, and CNN TL showcase low cost, low complexity, low delay, high accuracy, and high scalability; therefore, they must be used for high-performance skin disease detection. Therefore, researchers are required to use these models for use cases involving high-efficiency skin disease classification. In future, researchers can combine these models in order to obtain highly accurate classification performance for different skin disease types. Moreover, researchers can integrate multiple bioinspired techniques to further improve their classification performance via incremental learning operations.

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