Bulletin of Business and Economics, 13(1), 673-682
https://bbejournal.com
https://doi.org/10.61506/01.00254

Ensemble Deep Learning Methods for Detecting Skin Cancer

Mahnoor Sardar[1], Muhammad Majid Niazi[2], Fawad Nasim[3]

Abstract

Skin cancer is a prevalent and potentially lethal disease. Early identification has a significant impact on the effectiveness of treatment outcomes. Deep learning (DL) algorithms have shown promising results in computer-aided diagnostic systems for detecting skin cancer. This study explores various types of skin cancer, including melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC). It proposes a method for detecting skin cancer using convolutional neural network (CNN) techniques, specifically the multi-model ResNet (M-ResNet) architecture. We used ResNet framework that can effectively handle deep networks and exhibits enhanced performance in detecting skin cancer. The suggested methodology employs a comprehensive pipeline to detect skin cancer. The dataset undergoes pre-processing operations, including image resizing, normalization, and augmentation techniques, to enhance the model's ability to generalize. The combination of several models results in enhanced accuracy, sensitivity, and specificity in skin cancer learning classification system (SC-LCS) tasks. The proposed framework has considerable potential in effectively detecting various forms of skin cancer, aiding in early-stage diagnosis and treatment.

Keywords: Convolutional Neural Network (CNN), Skin Cancer Detection, Multi-Model ResNet

1. Introduction

Skin cancer could be a type of cancer that starts in the skin's cells. It is the most prevalent type of cancer worldwide. There are several types of skin cancer, and each has unique traits, risk factors, and available treatments. Skin cancer can be classified into three categories:

BCC (Basal Cell Carcinoma): The most prevalent type of skin cancer. Usually, it appears as a small, shiny protuberance or knob on the skin that has obvious blood veins on its surface. BCC usually appears on areas of the skin, like the hands, neck, and face, that are exposed to the sun on a regular basis. Although it rarely proves fatal and grows gradually, prompt treatment is essential to stop it from spreading.

Squamous cell carcinoma (SCC): Sun presentation is also linked to SCC, which typically affects the hands, ears, lips, and face. It sometimes appears as a rough, dried-up area or as a solid, reddish bump. Even though SCC progresses more quickly than BCC and has a higher likelihood of spreading to other body regions if left untreated, it is still remarkably treatable when caught in its early stages.

Melanoma: Melanoma originates in melanocytes, the cells that give skin its color. This type of skin cancer could be more aggressive and perhaps fatal. Any part of the body, including areas that are rarely exposed to sunlight, can develop melanoma. It frequently manifests as a dark-colored, irregularly shaped mole or as an injury that varies in size, form, or color over time.

Melanoma can spread to other organs and be fatal if not detected and treated early.

the three main categories, there are other less common types of skin cancer such as:

Merkel cell carcinoma: Usually an uncommon and real type of skin cancer that appears as tough, glittery pimples or growths on the skin.

It grows quickly and is especially common in places exposed to the sun.

Kaposi's sarcoma: This type of skin cancer is often associated with immunological insufficiency, as in patients with HIV/AIDS. It creates skin lesions that are crimson or purple and can even damage internal organs.

Preventing skin cancer involves protecting your skin Excessive sun exposure can be avoided by applying sunscreen, wearing protective clothing, and avoiding tanning beds. Regular self-exams and professional skin checks can help detect skin cancer early, when it is most treatable. If you notice any changes to your skin, such as new growths, changes to existing moles, or other worrying symptoms, you should seek medical attention.

Certain body areas with more sun exposure, like the face, arms, legs, and neck, are vulnerable to skin cancer. Melanoma a dangerous form of skin cancer can develop from new or existing moles or warning signs include irregular shapes, uneven colors, and diameter over 6mm. Deep Learning systems that help diagnose diseases have shown positive outcomes. If you see changes in your skin, consult a skin doctor for evaluation. When it comes to identifying skin cancer, including melanoma, early location is crucial. With the use of these tools, dermatologists seeing therapeutic pictures of skin injuries can receive a momentary or scheduled result. This could decrease the need for unnecessary biopsies and expedite the diagnosis process.

It is imperative to understand that dermatologists' expertise should not be replaced by deep learning algorithms. These frameworks should be used by dermatologists as tools to help them assess and make decisions. In the unlikely event that you see any skin abnormalities, it is imperative that you seek medical attention right away because prompt detection and treatment of melanoma can significantly increase survival rates. (Adegun et al, 2021). When it comes to identifying skin cancer, including melanoma, early location is crucial. With the use of these tools, dermatologists seeing therapeutic pictures of skin injuries can receive a momentary or scheduled result. This could decrease the need for unnecessary biopsies and expedite the diagnosis process. It is imperative to understand that dermatologists' expertise should not be replaced by deep learning algorithms. These frameworks should be used by dermatologists as tools to help them assess and make decisions. In the unlikely event that you see any skin abnormalities, it is imperative that you seek medical attention right away because prompt detection and treatment of melanoma can significantly increase survival rates. It often appears as an irregularly shaped mole with many colors, uneven edges, and the ability to change size and appearance. Anywhere on the body, including the face, neck, chest, back, legs, hands, feet, and even the eyes (visual melanoma) or under the nails, can develop melanoma.

[1] Department of Computer Science, Superior University, Lahore 54770, Pakistan
[2] Department of Computer Science, Superior University, Lahore 54770, Pakistan
[3] Corresponding Author, Department of Computer Science, Superior University, Lahore 54770, Pakistan, fawad.nasim@superior.edu.pk

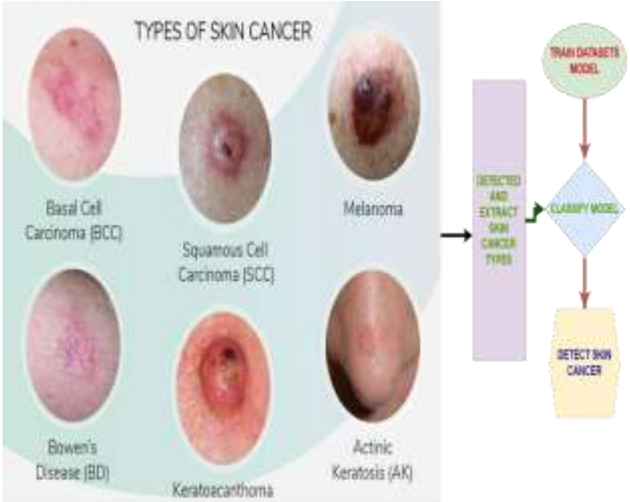

Figure 1: Step by Step Process of Detecting Skin Lesions Cancer with Different Types of Datasets

Moles, freckles or the formation of new growths. Early identification and treatment are essential for effective control of skin cancer. Skin cancer is a common type of cancer that helps store water and fat and also helps regulate body temperature. The largest issue with public health is typically cancer. On the skin, skin cancer may begin anywhere. Usually, exposed skin to the sun is where it begins. Despite the fact that There are multiple layers of skin, and skin cancer is common.

In this paper we discus, scientific approach to skin detection, emphasizing the importance of early skin cancer identification using multimodal ResNet and CNN technique. Traditional methods rely on visual examination by dermatologists, but recent advancements in deep learning, like the Region-based Convolutional Neural Network (ResNet-CNN), show promise in detecting skin cancer from medical images. ResNet-CNN combines object identification techniques with neural networks (Viriri et al,2021).

The epidermal subcaste is also known as the external subcaste. Non-melanoma skin cancer encompasses a wide range of skin cancer types, including primitive cell and scaled cell skin cancer. Skin cancer without melanoma Treatment response that is effective while being less intrusive in another place of the body where the skin is most detrimental. Carcinoma is one of the many types of skin cancer. Non-melanocytic lesions and cancer-like melanocytic lesions There are two types of lesions that are similar to primitive cell melanoma. Carcinoma is the deadliest and most aggressive kind of skin cancer, while it is less prevalent (Viriri et al,2021). if carcinoma skin cancer is not identified in time. It apparently takes over a group strongly and assaults another group of the body. Every year, more samples of cancer are found.

Melanoma Foundation (S. et al,2021) and A renowned cancer center time-consuming. Some deep-literacy strategies provide an answer to this issue. (Mahlougefer et al,2021) Deep literacy techniques in engineering carry out automated tasks. Deep Convolutional Neural Networks (DCNN) became popular recently as a result of this point. Researchers use DCNN to shed light on problems in a variety of domains, including the processing of therapeutic images. However, a recent suggestion to improve bracket performance is the group literacy system (Aljohani et al,2022), (Banerjee et al,2020). The use of Convolutional Neural Networks (CNN) has been recognized as a powerful tool. It's proposed for medical analysis in fields like histology and is designed for identifying details in biomedical images. It has also been applied in dermatology, ophthalmology, and radiology several times before. CNNs and other deep learning algorithms have to be adapted to and understood by non-experts due to their fast expansion. A sophisticated tool for a thorough assessment of the primers they offer an introduction to CNN's policies and procedures is provided (Demir et al,2019). Banerjee et al. developed a "You Simply See Once" (YOLO) technique for profound convolutional neural systems in (Dildar et al,2021). DCNN) procedures for skin lesions and digital pictures for cancer creation and diagnosis. More engaging and informative than the typical news style, these networks not only predict class confidence scores but also locate identified details within cells using bounding boxes. Goal - object. However, this study stands out through some objectification of the witty model. It includes two-stage segmentation by integrating graph concepts with L-type fuzzy.

The idea of using numbers and a minimum measurement tree, as well as the number line for the cancer region, is discussed. This relates to the contaminated area during the spotting birth process. Khan et al. introduced the Recruitment Algorithm (IMFO) to find the most distinct points. Points are generated Classification MMCA (Maximum Multiset Correlation Analysis) and KELM (Intense Kernel Learning Car) are the foundations of this method. Images containing the small segments of melanoma targeted parts are used by CNN for automated detection the diagnose.

CNN employments the little parcels of photographs with melanoma-affected ranges to prepare its robotized discovery calculation. Compared to high-quality feature-based methodologies, deep-learning-based frameworks perform superior at melanoma distinguishing proof and division. These procedures illustrated progressed localization and location capabilities for melanoma-affected skin parcels and can naturally calculate the difficult and cause usual of highlights straightforwardly from the contribution pictures. Furthermore, deep-learning strategies can rapidly discover skin injuries of different sizes indeed when there's clamor, obscuring, and an alter within the sum of light or color.

No melanoma skin cancers, the majority of skin cancer cases are caused by basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and sebaceous gland carcinoma (SGC). In contrast to melanoma, these tumors often arise in the epidermis of the skin and are less likely to metastasize. Skin cancers without melanoma are typically simpler to treat and have a greater cure rate when discovered early. Surgery, radiation therapy, topical medicines, and cryotherapy are all possible forms of treatment. Successful skin cancer therapy depends on early diagnosis. Identification of any questionable moles or skin lesions can be aided by routine self-examinations of the skin and dermatologist appointments. Knowing the warning symptoms of skin cancer, such as changes, is crucial changes in a mole's or skin lesion's size, shape, color, or texture, as well as any new growths or sores that don't cure. It's crucial to see a dermatologist for a thorough assessment if you observe any unusual skin changes. A biopsy may be taken by your dermatologist to evaluate if the skin changes are malignant or not. Early detection and treatment of skin cancer can significantly increase the likelihood of a good outcome and lower the risk of complications. (Duc et al,2022).

As We start by quickly distinguishing the assets in the ISIC database that are being transferred. At that point, a detailed defense is provided for the use of deep knowledge to examine designs in a probable test. The most prevailing type of tumor in the realm is skin malignancy, and profitable situation depends on early discovery. The labeling of skin malignancy, specifically melanoma and non-melanoma skin tumor's, has shown encouraging outcomes in recent years thanks to deep learning approaches. In one study, "Skin Cancer Detection with Deep Learning Techniques Using R-CNN Algorithm," To differentiate skin cancer, the region-based convolutional neural network (R-CNN) approach was investigated. An example of a deep learning system that uses object suggestions to identify regions of interest in a photograph is the R-CNN method. The study made use of skin lesion images from the International Skin Imaging Collaboration (ISIC) challenge. 2,000 images total from the collection showed 374 melanomas, 1,256 benign moles, and 370 cases of seborrheic keratosis. To further improve the accuracy of the demonstration, the images were refined and preprocessed. The exactness rate of the R-CNN computation used by the study's authors to analyze skin cancer was 88.5%. Additionally, they benchmarked their demonstration against other cutting-edge deep learning models and discovered that the R-CNN computation outperformed the others in terms of accuracy. According to the study's findings, the R-CNN algorithm may offer dermatologists support in their daily clinical job by serving as a useful tool for identifying skin cancer. The authors did note that further research is needed to evaluate the algorithm's suitability on larger datasets and to provide light on potential problems, like the requirement for master explanations and the need for preparation requires.

2. State-of-the-Art Analysis

CNN and RESNET are widely used for image recognition, classification, and cancer detection. They learn directly from data. CNN algorithms have been considered to have great accuracy in recognizing malignant skin lesions and have been trained on huge datasets of labelled photos. CNN demonstrated remarkable proficiency in image processing tasks and computer vision assignments, including localization, division, and classification identification. (Fujisawa et al,2019). On the other hand, the DL model gives points automatically Born and witnessed important achievements classic cation task for colorful medical images. (Watanabe et al,2019) Propose a new system using deep learning. They use two CNN models together in learning mode to automatically identify skin cancer, underestimating the disease. Also created were Craciars and Image Texture Points PH2, ISIC 2016, and ISIC 2019 datasets were used as distinct assessment criteria for the systems. (Gilani et al,2023). proposed the residual attention network, a novel deep literacy-based mode that separates 11 skin diseases trained on a dataset of 1167 histopathological images Collected by them in ten periods. They Use support point literacy to gain areas of interest with class activation images and diagrams. A visual description of Zhang's proposed network (Graver et al,1371) An If CentNet-B6 CNN model trained on the ISIC 2020 dataset was proposed as a model to explain cancer using deep literacy. They stated that they were the original users of this model for skin cancer. I applied a segmentation analysis of skin lesions using deep CNN in my exploration with transfer literacy employing sub-region Wind assessment criteria from Yuan et al.'s system (Harangi et al,2018). Yura. It has already been used in Very deep residual networks for performing automated carcinoma Identification on dermoscopic images (Harangi et al,2018).

Bee et al. hired Multistage fully convolutional neural network Dermoscopy image segmentation. Ulzy Orsik Dorji and others Skin tumor categorization using convolutional affecting animate nerve organs networks. Skin cancer spots were classified by Estava et al in a dermatologist study utilizing Deep Literacy (Zhang et al,2016). Mahmoud et al classified Cationization of skin lesions with deep nerves Network (Tang et al,2018). Group networks are commonly used in queries Now, to improve classification performance and Colorful models are usually trained in masses. The results are obtained by combining multiple predictions created a model that combines maturity and aggregation voting methods.

Table 1: List of Review Papers Written On Resnet Technique

Author	Year	Scope	Technique Resnet	Accuracy
Pacheco Krohling Et Al	2019	Skin cancer diagnose	DL-RESNET	87%
Lucirie Et Al	2021	Skin cancer classification	RESNET50-DL	93%
Adegun And Viriri	2021	Skin cancer analysis and detection	CNN-VGGNET-RESNET	89%
Dildar Et Al	2022	Skin cancer detection and classifier	ALEXNET-CNN	91%
Vippin Venugopal Et Al	2023	Skin cancer detection dermoscopic	NETV2-DNN	82.89%
Hossain Shahryar Et Al	2022	Multi class skin cancer classification	CNN-RESNET-INCEPTION3-VGG 16	97061%
Sachi Nandan Mohanty et al	2021	Comparison CNN based skin classifier	MOBILENET-RESNET-CNN	87.63%

(Iqbal et al,2021) proposed a group network. Skin Waste classification features are eradicated by acceptance Both models are unique and colorful, it is combined to achieve a better classification rate. The intended collection was estimated from seven predictions available datasets and detailed returns for ISIC-2018 Better performance compared to styles of Early detection of skin cancer Advanced Capsule Network (Caps Net) videlicet Fix Caps (Jain et al,2021). This learning process yields a fixed-length incorporate vector classified as melanoma-affected or -unaffected district with more obvious precision. The harmed locale is at that point portioned with variable estimates and bounds utilizing FKM, which can at that point be utilized for melanoma malady acknowledgment. We compared the proposed strategy to other later approaches utilizing the standard databases. Due to the faster-RCNN's compelling localization control and FKM's capacity to handle over-fitted preparing information, both the subjective and quantitative comes about illustrate that our system beats the other procedures.

Overall, the use of deep knowledge procedures, such as the R-CNN invention, in the identification of skin cancer, shows significant potential for enhancing the precision and effectiveness of diagnosis, eventually improving patient outcomes.

This article provides an overview of the most recent things that successfully diagnose skin cancer using various deep learning algorithms. This audit can be used as a foundation for developing profound learning algorithms for skin tumor detection that are more precise and efficient. As shown in Table 1, some reviews were enrolled in skin cancer discovery; for example, (Dildar, and Akram, 2021), (Duc et al, 2022), (Fujisawa et al,2019), (Watanabe et al,2019), and (Gilani et al,2023) reviewed deep learning algorithms for skin cancer discovery. Our article differs from others in this field since it examines the most recent current studies published in 2021 and 2022.The processes for physicians to appraise and resolve lesion countenances are time-consuming, complicated, emotive, and prone to error. This is largely due to the difficulty of representing skin lesions. Unambiguous labelling of wound pixels is owned by executing concept reasoning for skin lesion judgement and knowledge. The use of machine intelligence techniques in calculating vision has resulted in a significant advancement in calculating-aided demonstration and prognostic systems for skin tumor detection. As shown in Figure 3, image preprocessing and wound countenance classification are two of the key techniques employed to define the entire malignancy detection and illness process.

The rapid improvement in processing capability has resulted in significant advances in calculating apparition electronics, notably in the incident of deep knowledge models such as CNN. The first feasible finding of skin cancer is urgently required. According to (Graver et al,1371), the one who serves different young victims with skin tumor, skin tumor is the second most common tumor (after conscience cancer) in daughters between the years of 30 and 35, and the final common malignancy in wives between the ages of 25 and 29. Early skin cancer detection using deep knowledge surpassed human physicians in numerous computer fantasy competitions (Graver et al,1371),(Harangi et al,2018), resulting in lower death rates. By using effective formulas, it is possible to take better and cutting-edge treatment and classification veracity Methods of deep knowledge (Harangi et al,2018),(Sun et al,2018).

2.1. Research Gaps

One question that has to be addressed in "Discovery of Skin Cancer Utilizing Profound Learning Procedures Utilizing ResNet-CNN Calculation" is the necessity for thorough research on the combination of ResNet and CNN calculations in the skin cancer detection process. While deep learning approaches such as CNN have shown promise in medical image analysis and models such as ResNet have shown success in feature extraction, there is a lack of research on the synergy between the two techniques, particularly for skin cancer diagnosis. The study intends to close this gap by delving into the capabilities of ResNet-CNN fusion and its potential to advance skin cancer injury recognition from restorative photos in terms of accuracy, interpretability, and efficacy. The paper fills a research gap by comparing the ResNet-CNN algorithm with others. Existing techniques were evaluated in terms of detection performance, especially in difficult cases, and also in terms of the possibility of practical deployment in real clinical conditions.

Table 2: Comparative analysis of datasets 2017-2020 with different model

Paper	Datasets	Model	Performance
Alenezi et al.,	ISIC 2019-2020	ResNet-101 SVM	96.15%-97.12%
Gouda et al.,	ISIC 2018	CNN	83.2%
Reise et al.,	HAM 10000 ISIC 2018	IN-SINET-UNET	94.54%
Rashid et al.,	ISIC 2020	MOBILE NET V2	98.20%
Khan et al.,	ISIC 2017-2018-2019	CNN	87.02% - 92.87%
Alwaked et al.,	Ham 10000	CNN-RESNET-50	85%
Abbas and gul et al.,	ISIC 2020	NESNET	97.7%

Rashid, as well as others. (Jiang et al,2021) proposed a transfer learning innovation hosted in MobileNetV2 for cutaneous melanoma classification developed using the ISIC 2020 dataset for cutaneous melanoma categorization. Rashid, as well as others. (Kassem et al,2021) employed more data to investigate the course contrast problem and achieved a 92.8% normal precision. Since it was evaluated only for diseased versus mild cases, the predicted model must be evaluated based on the multiclass classification. Six profound learning models were evaluated by (Kausar et al,2021) for the classification of skin threats: DenseNet201, MobileNetV2, ResNet50V2 (Khan et al,2021), ResNet152V2, Exceptions, VGG16, VGG19, and Google Net. Every model was prepared using 7164 ISIC 2019 faces by (Kausar et al,2021). With Google Net entirely smothered, the most notable test certainty of 76.09% was obtained, and the demonstration was evaluated as it were for bi-classification.

(Lucieri et al,2021) used useful space data with profound knowledge to develop a skin cancer classification method. According to the continuation hypothesis, White Cloak misery (BWV), a crucial trait in the diagnosis of melanoma, is identified by the use of amplification work. With 96.2% accuracy, YOLOv3, advanced by Energetic Convolution Part (YoDyCK) prepared at ISBI 2016, was used to classify skin cancer. Most skin cancer databases have been collected from fair-skinned, calm individuals from Western countries. Due to one-sided datasets, profound information models developed using representations from Western countries would not function well when applied to characters with exposed skin. By organizing the suggested legislation in accordance with the reality that Asian countries are numerically silent, this study addressed the problem of predisposition in skin damage datasets. Emir, as well as others. (Majtner et al,2018) divided faces after skin injury into two categories: mild and malignant. Classification was performed on the ISIC dataset using ResNet-101 and Inception-v3. The correctnesses obtained via ResNet-101 and Inception-v3, individually, were 84.09% and 87.42%. Jain among other people. (Nyiri et al,2018) imparted a model for the identification of skin tumors based on transfer learning. Jain, among others. (Nawaz et al,2022) evaluated six different learning transfer models, including VGG19, InceptionV3 (Mahmoud et al,2022) and ResNet50, Xception, InceptionResNetV2 (Rahman,et al,2022), Portable Net, and Xception, which achieved a capital validity of 90.48% across all models.

Every model was prepared using the HAM10000 dataset. Xception provides high fidelity, but the computing time at this study site was generated by different networks. MobileNet's accuracy was slightly lower than Xception's, but still substantial. There is less time to prepare. Skin cancer was classified and separated by Han et al. (Nyiri et all,2018).

Skin cancer ideas were enriched in the pre-manipulation phase using a local graph with dedicated colors with bars for principles of value forces (LCcHIV) input to the separation network. Khan, among others. (Staff et al,2016) used 10 layers of CNN to project a new deep knowledge based projection technique for skin damage separation. Faces were created for the classification challenge using pre-trained ResNet101 and DenseNet201. Khan, among others. used an improved version of worm flame innovation (IMFO) to select the final discriminative facial features, they were then classed using the Part Extraordinary Learning Machine (KELM) classifier and blended using multiset greatest proportionality (MMCA). The proposed technique's division activity was evaluated using ISBI.

Real-world deployment and validation: While numerous studies have reported promising results in controlled settings, there is a research gap in evaluating the performance and generalization capabilities of multi-model ResNet architectures in real-world scenarios. Conducting comprehensive validation studies involving diverse clinical settings, multiple institutions, and real-time deployment can bridge this gap and provide insights into the challenges and limitations of these models.

Incorporating auxiliary information and multimodal data: The incorporation of extra data into deep learning models can help them such as patient history, dermoscopic images, clinical metadata, or genetic data. Exploring the integration of such auxiliary information into the multi-model ResNet architectures can potentially improve the accuracy, reliability, and clinical relevance of skin cancer detection models.

This research gaps will contribute to the Deep learning approaches for skin cancer diagnosis, with a particular emphasis on the use of multi-model ResNet architectures. By addressing these issues, the field can get closer to developing robust and trustworthy models that will aid dermatologists in accurately and promptly identifying skin cancer.

3. Proposed Methodology

The following actions are often taken in order to implement this technique for using the ResNet-CNN calculation for skin cancer discovery: Deep learning algorithms, specifically the Convolutional Neural Network (CNN) algorithm using a multi-model ResNet technique, can be useful in identifying skin cancer. CNNs are frequently employed for image classification tasks and have demonstrated excellent performance in a number of medical imaging applications, including the diagnosis of skin cancer.

ResNet, often known as the "Residual Network," is a CNN design that allows the network to learn residual mappings, making it easier to train very deep networks. The accuracy and efficiency of skin cancer detection can be enhanced by combining multiple ResNet models. Here is a general outline of the steps involved in using the CNN algorithm with a multi-model ResNet approach for skin cancer detection. CNN architecture with ResNet as the foundation. ResNet models are made out of residual blocks that make deep network training effective. Depending on how hard the task is, you may layer different ResNet blocks and change the depth.

For training, divide the dataset into training and validation sets. the multi-tasking training set Multimodal ResNet CNN using the labeled skin images. During training, use techniques like batch normalization and dropout to improve generalization and prevent over fitting. Optimize the model using appropriate loss functions (e.g., cross-entropy) and optimization algorithms (e.g., stochastic gradient descent). CNNs are an artificial neural network type that have been demonstrated to be incredibly effective in fields for example, picture recognition and categorization (Chen et al,2022). Every ANN has at least three layers: an input layer that takes the input dataset, a hidden layer that was trained using the input layer's inputs, and an output layer that outputs based on the inputs given. CNNs are trained using labelled datasets with acceptable classifications. CNNs are made up of two layers: a hidden layer that accumulates features and a fully linked layer that conducts classification. CNNs learn the association between class labels and input objects through the hidden layer.

Skin lesions may be categorized using CNNs in two separate ways. A CNN, for example, might be used as a feature extractor for a big dataset like ImageNet (Banerjee et al,2020). In this situation, classification is performed by another classifier, such as support artificial neural networks, vector machines, or k-nearest neighbours. The second benefit of adopting end-to-end learning is that a CNN may learn the link between raw pixel data and class labels directly. Feature extraction, unlike the machine learning workflow, does not require human participation and is now considered as a vital stage in the classification process. Learning from scratch and transfer are the two main forms of end-to-end learning processes used to train the CNN.

3.1. Datasets

Resnet50: It's possible that Resnet-50 is a 50-layer scheme (Tomita et al,2019). There were several issues that analysts ran into when attempting to apply the adage "the more profound the superior" to profound learning approaches. This notion that "the more profound the organize, the higher the network's productivity" was refuted by a 52-layer profound arrange that functioned inefficiently in comparison to systems with 20–30 levels. Specialists built Resnet-50, a leftover learning component from the CNN program. To account for the residual unit, a conventional layer with a skip connection is utilised. A skip connection can be used to connect the output of one layer to the incoming signal of another. The 2015 LSVRC2015 competition was won by a 152-layer model trained with residuals units. Because to its unique residual structure, it has fewer learning curves. A top five false-positive rate of 3.6% is possible with this equipment.

3.2. Model for Proposed Approach

Calculation 1 describes how to use a CNN show and images from a picture information store to provide relevant and discriminative property explanations for the cancer discovery method. An introduction to the dataset is given at the outset. Additionally, the fundamental architecture and preprocessing methods for the suggested model's implementation are explained in depth.

3.2.1. Process and Sequence of Proposed Solution

DL models confront substantial challenges due to the vast number of hyper parameters and structures that must be addressed (such as learning rate, number of frozen layers, batch size, and number of epochs). The effectiveness of the suggested systems was investigated over a range of hyper parameter values. Figure 7 displays the suggested CNN model's three layers. The skin cancer detection system used the transfer DL strategy to train informative and discriminative feature representations from preprocessed pictures in the image datasets, as shown in Figure 2.

Algorithm 1: Functions of the proposed mechanism
If barcapitalb is ig is the image, ig€ is the image enhancement algorithm (ESRGAN), rt is the rotation, sc is the scaling, rl is the reflection, and sh is the shifting technique, then

Fill in the blanks with: "Lesion image barcapitalb" is a lesion image.
Outputs include the confusion matrix, accuracy, precision, ROC, F1, AUC, and recall.
First, look up (barcapitalb).
Step 2: Put (ppr (ig)) to use
_ Operate (ig€) 2.2. Aug (ig) in terms of rt, sc, rl, and sh
2.2.1. execute rt
2.2.2. whole sc
2.2.3. complete rl
2.2.4. execute sh
(ig)/224*24*3 (2.3) resize
2.4 Normalize the pixel value (ig) for the [0,1] interval.
Step 2: Split the dataset and do validation, testing, and training.
Step 3: Create a CNN model.
In step four, retrained models (ResNet, Inception, and Inception ResNet) are trained.
Adjust model parameters as needed (freeze layers, learning rate, epochs, batch size).
In step 5, compute the VPM (confusion matrix, accuracy, precision, ROC, F1, AUC, and recall).
Step 6: Evaluate the work that has previously been completed.

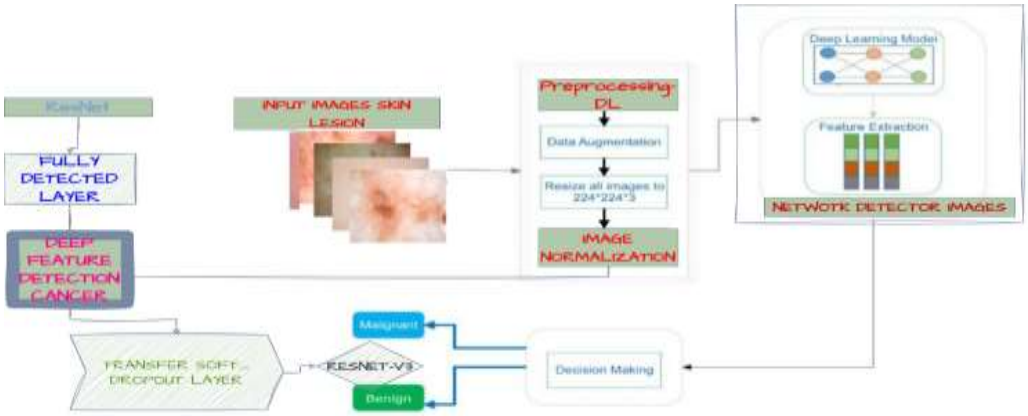

Figure 2: Proposed structure of skin cancer detection using CNN-ResNet Technique

Case in point: Inception of ResNet: This network has 164 layers and can categories pictures into 1000 different items. As a result, the network has gathered an extensive collection of feature descriptors. The network gives a set of classifiers in exchange for a 299 by 299-pixel image as input. To classify hyperspectral pictures, the Resnet50 and Inception frameworks were integrated into a single model. The Inception ResnetV2 convolutional neural network was trained using over a million photographs from the ImageNet database. There is overall:
Index for Parameterization and Experimental Evaluation
The performance of the suggested DL systems was demonstrated using simulations on the ISIC2018 dataset, and the results were compared to the state of the art. Tensor Flow Keras software from the proposed technique was tested on a Linux desktop with an RTX3060 GPU and 8GB of RAM. Figure 8 shows the 80:20 portion of setting up and testing settings. The testing set contained 360 good and 300 horrifying images, while the arrangement set contained 1760 amazing and 1773 painful images.

3.2.2. Datasets

The 2018 dataset from the Around the World Skin Imaging Collaboration, sometimes referred to as the ISIC 2018 dataset, is a potentially widely used set of carefully selected images of skin wounds that are meant to be used in the search for skin cancer. It includes a variety of dermoscopic images illustrating many types of skin lesions, including both dangerous and generous diseases. The dataset provides a valuable resource for training and evaluating machine learning models, like the ResNet-CNN model, for accurate and efficient skin cancer detection.
The ISIC 2018 dataset is being used by the analysts to develop and evaluate their models' ability to distinguish between various categories of skin injuries. The collection includes enlarged images that show each injury's ground truth name. These names help set up the computation to identify important details and patterns associated with various types of skin damage. The ResNet-CNN computation related to skin cancer detection uses the ISIC 2018 dataset as a baseline to evaluate the model's performance. Analysts can grade the algorithm's exactness, affectability, specificity, and other execution metrics by preparing a computation on a subset of the information set and evaluating it on a partitioned test subset. This dataset contributes to the development of more dependable and efficient teaching tools for medical professionals It expands research on the ResNet-CNN computation's potential for precisely differentiating skin cancer lesions.
Based on data from the 2016, ISBI 2017, ISIC 2018, and PH2 datasets, the predicted appearance achieved the highest rank classification exactness of 90.67% on the PH2 dataset and the highest rank classification accuracy of 90.67% on the

HAM10000 dataset. The presented show provides a high-quality division show on PH2, with approximately 200 outlines; testing on better datasets can evaluate the impact of the proposed format choices. Adegun, as well as others. (Mahmoud et al,2022) hypothesized that the order of separation of skin lesions generates a sufficiently convolutional connected system. To create the segmentation behavior, a probabilistic show using a Gaussian substance was paired with a lightweight coder-decoder deep learning demonstrate; this helped to fine-tune the face borders of the skin injuries. The predictive show developed for PH2 and ISBI 2016 achieved 98% accuracy. The proposed model was built with a heap parameter of 6.97, which is much lower than the next smallest of the 10 million DSNet dissection constraints used to separate skin cancer representations, although it took longer to train.

Figure 3: Datasets Upload ISIC2018

The proposed training set was made out of an 80% randomly distributed collection of lesion photos. This set was used for all testing. Throughout the learning process, the remaining 10% of the data was used for verification. Weight combinations with the highest accuracy values were kept. The proposed design was connected to the ISIC2018 dataset using the Adam optimizer. It makes use of a learning rate technique that reduces learning when it is idle for an extended period of time (approval tolerance). Additionally, we used a bunch rebalancing approach to reduce the authority of illness types during bunching.

4. Experimental Results

4.1. Comparison Adapted Model Effectiveness

To analyses the efficacy and potential of CNNs, 8 skin disorders were classified in this study. ResNet 152, Dense Net 201, and Inception v3 are examples of modern trained architectures. This dataset includes basal cell carcinoma, melanoma, actinic keratosis, vascular lesions, melanocytic nevi, benign keratosis, atypical nevi, and dermatofibroma. 10135 dermoscopic photos, 10015 HAM10000 images, and 120 PH2 images were employed. They outperformed dermatologists by 11%, according to the findings. Dermatologists' AUC ROC values for basal cell carcinoma and melanoma are 88.82% and 82.26%, respectively, however the greatest values are 99.30% (Dense Net 201) and 94.40% (ResNet 152). Dense Net is also used for general classification 201 got the greatest Both the micro and macro AUC averaged values of 98.79% and 98.16% are acceptable.

Experts have examined and evaluated the veracity of the data pertaining to the accuracy rate of computer-assisted procedures (Nasim et al,2023). We searched Springer Connect, Science Coordinate, and the IEEE database. It was discussed what the basic limitations of the methodologies for classifying and dividing up skin injuries were. In (Damasevicius et al,2021), a unique method for identifying melanoma skin cancer was discovered. Utilizing a nonlinear implanting implantation complex, synthetic images of melanoma were generated. An updated set of skin melanoma datasets was produced by applying the information expansion approach to dermatoscopy photos from the publicly available PH2 dataset. The photographs that had been altered were used as input for the profound learning computation. The trials showed that melanoma detection accuracy greatly increased (92.18).

Table 1

Ensembles Again Using Several Epochs Results

Batch Size	Run 1	Run 2	Run 3
1	0.8182	0.8	0.8136
4	0.8318	0.8257	0.8121
11	0.8061	0.7909	0.8091
16	0.7879	0.7879	0.7985
44	0.7864	0.7969	0.7985

A digital dermatoscopy image's skin melanoma (SM) area might be extracted using the VGG-ResNet technique, as indicated in (Nasim et al,2023). Critical performance criteria were determined by comparing the generated segmented SM to the ground truth (GT). Using the common ISIC2016 database, the proposed technique was evaluated and validated. Skin cancer has been classified using a combination of human and machine intelligence. 112 German

The table shows the average accuracy of the CNN model while utilizing the ISIC dataset with different parameters, such as the optimizer (Adam) and the learning rate (1 106).

Table 2 shows the CNN model's average accuracy while utilizing the ISIC dataset with various parameters, including the optimizer (Adam) and the learning rate (1 104).

Physicians and a CNN reporter classified 300 skin lesions with biopsy data into five categories. The two independently acquired sets of diagnoses were combined using gradient boosting to produce a single classifier. The multiclass accuracy

achieved by man and machine was 82.95% (Khan et al,2021). Both benign and malignant tumours may be found using the deep learning-based ResNet approach (Ahmed et al,2021).
The method was tested on HAM10000 pictures Under similar circumstances, (ISIC 2018), (ISIC 2019), and (ISIC 2020). As a result, when applied to the ISIC 2018, Using the ISIC 2019 and ISIC 2020 datasets, the ResNet system outperformed the other approaches, with individual precision rates of 94.59%, 91.89%, and 90.549%.

Table 2

Assemble Using Several Epochs

Batch Size	Run 1	Run 2	Run 3
2	0.7818	0.7606	0.7011
5	0.7636	0.7833	0.7363
11	0.7363	0.75	0.7439
21	0.7939	0.7727	0.7636
44	0.7651	0.7363	0.7363

4.2. Average Collaboration Strength Methodology

The collection percentage utilized during preparation is categorized from 2 to 32, and it determines the number of samples processed in each preparation step. Different assortment sizes were tested in tandem to improve the preparation procedure and ensure proficient use of computing assets. Secondhand education rates for model preparation range from 1-104 to 1-106. A hyperparameter that monitors the step measure at which the show recovers appeal limitations throughout the planning handle may be the information rate. Different knowledge rates were tested to determine the most dependable rate that leads to Better model act and speedier union. The accomplishment of the presented schemes on the ISIC2018 dataset was completely appraised by administering numerous assessments and preparing the models under varied configurations. This allowed for a thorough examination of the models' veracity, inference, and appropriateness for skin damage classification.
ResNet50, Initiation, and Initiation ResNet were refined by stabilizing shifting sums of layers in order to demand the highest level of accuracy. We created a demonstration group using different runs (three runs for the same conditions) to make sure the models were generated using similar parameters throughout runs 1 through 3 (as shown in Tables 3 and 4). Because the weights were randomly initialized at the start of each run, the accuracy numbers fluctuated from run to run. Only the best-performing run's results were kept for analysis and comparison.
Tables 3 exhibit the accuracy results for the proposed CNN model, demonstrating the performance obtained by fine-tuning and assembling the various architectures (ResNet50, Inception, and Inception ResNet) with their corresponding frozen layers. These tables show how fine-tuning different layers affected the model's accuracy and how the model ensemble's performance was reached over time. The accuracy findings suggest that the suggested CNN is effective in detecting skin injuries and highlight the significance of fine-tuning and collaboration in order to achieve high accuracy rates.

4.2.1. Average Collaboration Strength Comparison with Other Methods

To better demonstrate the offered method's liveliness, a comparison of its viability to that of existing courses of action was made.

Table 3: Comparison of additional designs

Reference	Dataset	Model	Accuracy
H.M Ayan	ISIC2018	VGG19_2	76.60%
D.Tanjar	ISIC2016	VGGNet	78.60%
Hooker J.M.	ISBI2017	Alex Net + VGGNet	79.90%
Fuzzel L.N.	2-ary, 3-ary, 9-ary	DenseNet	82%
Jaiswal A.K.	HAM10000	AlexNet	84%
Proposed	ISIC2018	CNN	83.10%
Proposed	ISIC2018	Resnet50	83.60%
Proposed	ISIC2018	Resnet50-Inception	84.10%
Proposed	ISIC2018	Inception V3	95.70%

Demonstrates that our design outperformed other networks in terms of performance. In the predicted approach, the Inception model outperformed the existing models with an overall veracity rate of 95.7%.
Fine-tuning the networks enhanced the accuracy of all four models much more. When compared to ResNet50 and Inception ResNet, the accuracy of InceptionV3 increased the greatest. Our findings show that deep networks perform better when calibrated on a smaller sample in comparison to shallow networks. Figures 8 and 7, which show the confusion matrices and mathematical data, prove that the techniques used were adequate and acceptable. Overall, our strategy, which combines CNNs with fine-tuning and different architectures, has proved to be useful in detecting skin lesions with high accuracy. The use of many models, each with its own set of strengths and generalizability, adds to the success of our suggested approach.
Skin lesions may be categorized using CNNs in two separate ways. A CNN, for example, might be used as a feature extractor for a big dataset like ImageNet (Tomita et al,2019). In this situation, classification is performed by another classifier, such as support artificial neural networks, vector machines, or k-nearest neighbours. The second benefit of adopting end-to-end learning is that a CNN may learn the link between raw pixel data and class labels directly. Feature extraction, unlike the machine learning workflow, does not require human participation and is now considered as a vital stage in the classification process. Learning from scratch and transfer are the two main forms of end-to-end learning processes used to train the CNN.

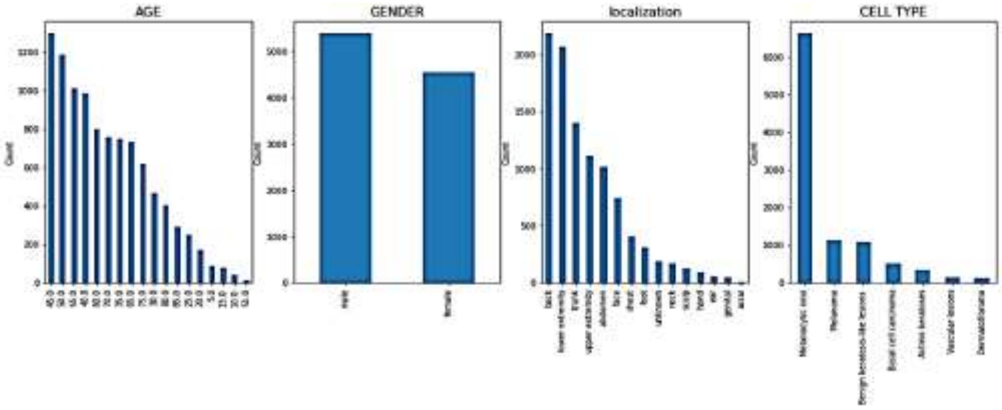

Figure 4: Analysis and Detect Age Type Localization of Skin Cancer Disease Based Approach

It is evident from the findings that the suggested process might be applied in practical contexts to help radiologists use injury photos to more precisely identify cancer contaminations. Deep learning models like CNN, ResNet50, Beginning, and Beginning ResNet can greatly reduce the workload for radiologists. With the application of this method, radiologists will be able to depend on the models' capacity to analyse and categorise skin lesion pictures, giving them with additional assistance and improving their diagnostic accuracy. This technique has the potential to result in earlier identification and more precise diagnosis, thereby improving patient outcomes. Deep learning techniques for classifying skin injuries improve efficiency of the process, allowing radiologists to focus their knowledge on more urgent cases while reducing the time and effort required for a typical skin injury classification analysis. This derangement of the symptomatic approach may increase effectiveness and advance the application of treatment resources.

5. Conclusion and Future Work

By increasing brightness and reducing impact, the suggested structure uses figure expansion techniques to improve damage figures. ResNet50, InceptionV3, and Inception ResNet were trained using preprocessed lesion healing figures to avoid overfitting and enhance the overall portrayal of the deep education plans. The bureaucracy execution was surveyed using the ISIC2018 dataset. The expected process yielded an accuracy percentage of 95.7% for the Initiation Test, which is the same as determining the validity of dermatologists. The primary offering and modification of this study protest using ResNet as a preprocessing step.

While reviewing other studies that perform skin injury discovery established photographs, few systems provided by many authors were similar, while potential choices were questioned to equal due to variances in their techniques and methods the quantity of secondhand dossier. It is strongly advised to employ genuinely suitable standards and offer detailed notification of the designs secondhand to ensure future publishing correspondence. Furthermore, future study should investigate fact-finding negative factors such as vulnerability to adversarial assaults. Additionally, to avoid bias and obtain more accurate findings, a negative dossier (depicting non-malignant lesions) is supplied alongside favorable data (malignant lesions). This technique contributes to achieving an equalized appraisal of bureaucracy's portrayal. It would be beneficial if future articles used these criteria to assess the accuracy of CNN in skin injury detection and classification indications. By resolving these approvals and concerns, the area of skin tumours discovery employing deep knowledge forms will be able to progress further and provide more reliable and trustworthy findings.[4]

References

Adegun, A. A., Viriri, S., & Yousef, M. H. (2021). A probabilistic situated deep knowledge model for skin wound separation. *Applied Sciences, 11*, 3025.

Adegun, A., & Viriri, S. (2021). Deep learning methods for skin wound reasoning and melanoma malignancy discovery: A survey of brand new. *Artificial Intelligence Review, 54*, 811–841.

Adigun, A., & Viriri, S. (2021). Deep learning techniques for skin lesion analysis and melanoma cancer detection: A survey of state-of-the-art. *Artificial Intelligence Review, 54*, 811–841.

Alizadeh, S. M., & Mahlougefer, A. (2021). Automatic detection of skin cancer: Convolutional neural networks and texture functions. *International System Image, 31*, 707–695.

Aljohani, K., & Turki, T. (2022). Automatic classification of melanoma skin cancer using deep convolutional neural networks. *Aj, 3*, 512–525.

Banerjee, S., Singh, S. K., Chakraborty, A., Das, A., & Bag, R. (2020). Melanoma diagnosis using deep and fuzzy learning logic. *Diagnostics, 10*, 577–586.

Bian, X., Pan, H., Zhang, K., Li, P., Li, J., & Chen, C. (2022). A skin wound representation categorization design established the extension and deep knowledge hypothesis. *Multimedia Tools and Applications, 81*, 16409.

Demir, A., Yilmaz, F., & Kose, O. (2019). Early detection of skin malignancy using deep knowledge architectures: ResNet-101 and begin-v3. *Proceedings of the 2019 Medical Technologies Congress (TIPTEKNO)*, (pp. 1–4). Izmir.

Dildar, M., Akram, S., Irfan, M., Khan, H. U., Ramzan, M., Mahmood, A. R., . . . Mahnashi, M. H. (2021). Skin tumor discovery: A review using deep learning methods. *International Journal of Environmental Research and Public Health, 18*, 5479.

Dildar, M., Akram, S., Mahmood, A. R., Mahnashi, M. H., Alsaiari, S. A., Irfan, M., . . . Alraddadi, M. O. (2021). Skin cancer detection: A review using deep learning techniques. *International Journal of Environmental Research and Public Health, 18*, 5479.

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

Duc, N. T., Lee, Y. M., Park, J. H., & Lee, B. (2022). An ensemble deep learning for automatic prediction of papillary thyroid carcinoma using fine needle aspiration cytology. *Expert Systems with Applications, 188*, 115927.

Fujisawa, Y., Otomo, Y., Ogata, Y., Nakamura, Y., Koriyama, N., O'Hara, K., . . . Watanabe, R. (2019). Deep-learning-based, computer-aided classifier developed with a small dataset of clinical images surpasses board-certified dermatologists in skin tumor diagnosis. *British Journal of Dermatology, 180*, 373–381.

Fujisawa, Y., Otomo, Y., Ogata, Y., Nakamura, Y., Koriyama, N., O'Hara, K., . . . Watanabe, R. (2019). Deep-learning-based, computer-aided classifier developed with a small dataset of clinical images surpasses board-certified dermatologists in skin tumor diagnosis. *British Journal of Dermatology, 180*, 373–381.

Gilani, S. Q., & Marques, O. (2023). Skin injury studies using fruitful adversarial networks: A review. *Multimedia Tools and Applications*, 1–42.

Graver, M., Schwartz, S., & Chabner, B. (1371). National Cancer Institute: Cancer Drug Development Program. *Oncor Seminar, 19*, 622–638.

Harangi. (2018). Classification of skin lesions based on a set of deep folds neural network. *Journal of Biomedicine, 86*, 25–32.

Harangi, B. (2018, October). Classification of skin lesions based on a set of deep folds “neural network”. *Journal of Biomedical Notice, 86*, 25–32.

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Identity weighting in deep residual networks. *14*, 630–645.

Hu, Z., Tang, J., Wang, Z., Zhang, K., Zhang, L., & Sun, Q. (2018). Deep learning for image-based cancer detection and diagnosis: A survey. *Pattern Recognition, 83*, 134–149.

Iqbal, S., Siddiqui, G. F., Rehman, A., Hussain, L., Saba, T., Tariq, U., & Abbasi, A. A. (2021). Prostate cancer detection using deep learning and traditional techniques. *IEEE Access, 9*, 27085–27100.

Jain, S., Singhania, U., Tripatie, B., Nasr, E. A., Aboudaif, M. K., & Kamrani, A. K. (2021). Knowledge transfer-oriented deep learning for skin malignancy categorization. *Sensors, 21*, 8142.

Jiang, S., Li, H., & Jin, Z. (2021). Visually interpretable deep learning frameworks for diagnosis of skin cancer based on histopathological imaging. *IEEE Journal of Biomedical and Health Informatics, 25*, 1483–1494.

Kassem, M. A., Hosny, K. M., Damasevicius, R., & Eltoukhy, M. M. (2021). Machine learning and deep learning methods for skin lesion classification and diagnosis: A systematic review. *Diagnostics, 11*, 1390.

Kausar, N., Hameed, A., Sattar, M., Ashraf, R., Imran, A. S., Abidin, M. Z., & Ali, A. (2021). Multi-class categorization of skin tumors using an ensemble of calibrated deep learning models. *Applied Sciences*, *11*, 10593.

Khan, M. A., Sharif, M., Akram, T., Damasevicius, R., & Maskeliunas, R. (2021). Segmentation and multiclass of skin lesions classification using deep learning features and improved moth flame optimization. *Diagnostics, 11*, 811.

Lucieri, A., Dengel, A., & Ahmed, S. (2021). Deep Learning Based Decision Support for Medicine - A Case Study of Skin Cancer Diagnosis. *arXiv*.

Majtner, T., Bajic, B., Yildirim, S., Yngve Hardeberg, J., Lindblad, J., & Sladoje, N. (2018). A set of convolutional neural networks for dermatoscopy image classification. *arXiv*. doi:1808.05071

Nawaz, M., Mahmoud, Z., Nazir, T., Naqvi, R. A., Rahman, A., Iqbal, M., & Saba, T. (2022). Skin Cancer Imaging Microscopic Research and Technology. *Journal of Electron Microscopy Technique, 85*, 339–351.

Nyiri, T., & Kiss, A. (2018). New Methods Group for Dermatology. 438–448.

Pacheco, A. G., & Krohling, R. A. (2019). Recent advances in deep learning used to discover skin malignancies. *arXiv*.

Rashid, J., Ishfaq, M., Ali, G., Saeed, M. R., Hussain, M., Alkhalifah, T., . . . Samand, N. (2022). Discovery of skin cancer by education transfer method. *Applied Sciences, 12*, 5714.

Staff, T. S. (2021). What is the difference between melanoma and non-melanoma skin cancer?

Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. (2016). Rethinking the original design for a computational concept. 2818–2826.

Tomita, N., Abdullah, B., Wei, J., Ren, B., Suriawinata, A., & others. (2019). Attention-based deep neural networks for diagnosis of esophageal cancerous and precancerous tissue in histopathological slides. *JAMA Open Network, 2*, 1914645.

Unver, H. M., & Ayan, E. (2019). Skin lesion segmentation in dermoscopic images with combination of YOLO and grab cut algorithm. *Diagnostics, 9*, 72.

Vaishnava, K., Ramadas, M. A., Chanalya, N., Manoj, A., & Nair, J. J. (2021). Deep learning approaches for detection of COVID-19 using chest X-ray images. *Proceedings of the 2021 Fourth International Conference on Electrical, Computer and Communication Technologies (ICECCT)*, (pp. 1–6). Piscataway.

Wang, S., Su, Z., Ying, L., Peng, X., & Zhu, S. (2016). Acceleration of magnetic resonance imaging with deep learning. *Proceedings of the 13th Symptom on Biomedical Imaging (ISBI)* (pp. 514–517). Prague: IEEE.

Zegedy, C., Ioffe, S., Vanhoucke, V., & Alemi, A. (2017). Start-v4, start-ResNet and the impact of residual relations on knowledge. *31*.

Zhang, R. (2021). Melanoma detection using convolutional neural networks. *Proceedings of the IEEE International Conference on Consumer Electronics*, (pp. 75–78). New York.

Nasim, F., Masood, S., Jaffar, A., Ahmad, U., Rashid, M. (2023). Intelligent sound-based early fault detection system for vehicles. *Computer Systems Science and Engineering*, 46(3), 3175-3190.

Nasim, F., Yousaf, M.A., Masood, S., Jaffar, A., Rashid, M. (2023). Data-driven probabilistic system for batsman performance prediction in a cricket match. *Intelligent Automation & Soft Computing*, 36(3), 2865-2877.