Skin Cancer Detection Using Deep Learning Techniques

Ragavendra S[1], Subhash S[2], Nishanth B[3], Chandan J[4]

1 Assistant Professor, Department of Computer Science and Engineering, Jnanavikas Institute of Technology, Karnataka,India

2Undergraduate Student, Department of Computer Science and Engineering, Jnanavikas Institute of Technology, Karnataka, India

3Undergraduate Student, Department of Computer Science and Engineering, Jnanavikas Institute of Technology, Karnataka, India

4Undergraduate Student, Department of Computer Science and Engineering, Jnanavikas Institute of Technology, Karnataka, India

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***Abstract** – Less people are aware of the symptoms of skin illness and how to prevent it, making it one of the deadliest forms of cancer. The aim of this study is to identify and categorize different forms of skin cancer using machine learning and image processing techniques. We produced a pre-processing image for this endeavor. We lowered the dataset's size,*

To fit the needs of each model, the photos were resized and had their hairs removed. The EfficientNet B0 skin ISIC dataset was trained using pre-trained ImageNet weights and modified convolution neural networks.

Keywords- Disease Detection, Image Processing ,YOLOR, EfficientNet B0, Quantification

INTRODUCTION

Skin cancer, which is on the rise globally, is the sixth most common cancer. Normally, tissues are made up of cells, and tissues make up the skin. Consequently, cancer is caused by abnormal or unregulated cell development in connected tissues or other nearby tissues. Numerous factors, such as UV radiation exposure, a weakened immune system, a family history of the disease, and others, may affect the development of cancer. These types of cell development patterns can appear in both benign and malignant tissues. Benign tumours, which are cancerous growths, are sometimes mistaken for minor moles. Malignant tumours,on the other hand, are treated like a cancer that may spreadfatally.

The body's other tissues could also be harmed by them. Basal cells, squamous cells, and melanocytes are the three types of cells that make up the skin's outer layer. These are at fault for the tissues' development of cancer.

The three fatal forms of skin disease (SCC) are melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC).

Vascular lesions, actinic keratosis (AK), benign keratosis, dermatofibroma, and melanocytic nevus are a few examples of further types. Melanoma is the most dangerous type of cancer because it can come back even after treatment. The United States and Australia have the highest rates of skin cancer.

RELATED WORK

The study by YaliNie& team, Automatic Melanoma Yolo Deep Convolution Neural Networks for Detection" [1] describes yolo approaches based on DCNNs that are used to identify melanoma. For melanoma detection in lightweight system applications, they provide important advantages. YOLO's mean average precision (mAP) can go as close to 0.82 with just 200 training photographs.

A Convolution Neural Network and YOLO-based Real- Time Skin Cancer Detection System is another paper by Hasna Fadhilah Hasya et al. For the benefit of patients who do not wish to wait for the results of hospital lab tests, the author of this research [2] created a method for real-time skin cancer detection. The goal is to create a skin cancer detection algorithm that will make it easier and more efficient for clinicians to analyze skin cancer test findings.

The Convolution Neural Network (CNN) is utilized to process and aggregate skin cancer picture data, and YOLO is the real-time system. YOLOV3 has a 96% overall accuracy rate and a 99% real-time accuracy rate.

Performance Evaluation of Early Melanoma Detection According to the research of R.S. ShiyamSundar and M. Vadivel [3], one of the methods that uses the MVSM classifier is the Skin Lesion Classification System. Melanoma is the most common kind of skin disease. Early disease detection is the key to reducing the disease's effects. Actinic keratosis, squamous cell cancer, basal cell cancer, and seborrheic verruca are the five forms of skin lesions that are categorized and taken into account by the proposed method.

Ferreira, P. M. and colleagues provide a basic concept for an annotation tool that can improve dermoscopy datasets in their publication "A tool for annotating dermoscopy datasets" [5]. Create a ground truth image under dermatologist supervision and apply manual segmentation approaches to automate categorization and segmentation procedures. Any detection system's feature extraction phase is essential. A posteriori boundary edition, region labelling, segmentation comparison, border reshaping, multi-user ground truth annotation, manual segmentation, image uploading and display are some of the main features of this programme.

In their study, Vedantin Chintawar and Jignyasa Sanghavi examined various feature extraction techniques and recommended the technique that would be most useful for applications requiring the detection of skin cancer. Enhancing Feature Selection in Skin Disease Diagnosis Systems.

Competencies" [6]. The first and most crucial step is the method of hair removal, and the next is segmentation utilizing the OTSU procedure. Aspects including wholeness, luminosity, fast corners, solidity, shape skewness, and border skewness are all retrieved by the projected system.

Specific traits must exist, in accordance with Hutokshi Sui's "Extraction of texture features for melanoma"[7]. In this study, the texture of skin lesions is examined using greyscale photos rather than colour profiles. SVM is utilized as a classifier to distinguish between different types of skin cancer, while GLCM is used to extract features.

METHODOLGY

DATASET: In this study, we employed a bespoke datasetmade up of 3000 Google photos and samples of skin cancer.

METHOD: YOLOR is an evolution of the machine learning program "You Only Learn One Representation". The authorship, design, and model architecture of contemporary object identification machine learning algorithms like YOLOR differ from those of its predecessors.

A "unified network for concurrently encoding implicit and explicit information" is how YOLOR describes it. These results support the findings of the YOLOR study article "You Only Learn One Representation: Unified Network for Multiple Tasks," which emphasizes the value of leveraging implicit knowledge.

A functional diagram used to demonstrate the advised method is shown in Figure 1. Each block is explained in great detail below.

Skin Cancer Image	***Number of Images***		
	Train	***Test***	***Valid***
Actinic keratosis	214	214	214
Basal_cell_carcinoma	116	116	116
Dermatofibroma	168	168	168
Melanoma	504	504	504
Nevus	116	116	116
Pigmented_benign_keratosis	528	528	528
Seborrheic_keratosis	130	130	130
Squamous_cell_carcinoma	242	242	242
Vascular_lesion	103	103	103
Total	***2121***	***2121***	***2121***

Table 1 : Distribution of Dataset images

- **Input Image:** The suggested method is based on the ISIC 2019 Challenge data set, which consists of nine classes, each with eight images. Researchers at the University of Bristol created the proposed system using a dataset of high-resolution dermoscopic images.

- **Pre-processing:** The technique utilized to get the photos must contain a number of discrepancies. As a result, this is what the pre- main processing aims to achieve. By cropping or removing the background or other distracting components, the image's quality,clarity, and other attributes are improved in thefollowing step. The primary pre-processingprocedures are noise reduction, imageenhancement, and grayscale conversion. The photographs that will be used in this suggested approach are first made grayscale. The image is then improved and noise is removed using the median and Gaussian filters. The dull razor is combined with an abundance of hair removal from skin blemishes. The goal of image enhancement is to make an image better by increasing its visibility. The majority of skin lesions often consist of body hair, which makes accurate and precise classification challenging. As a result, the dull razor method is used to remove undesirable hair from photographs. The following tasks are typically accomplished with the Dull Razor method:

- The grayscale morphological procedure was utilized to locate the hair on the skin lesion.

- By using bilinear interpolation, it finds the hair pixel, determines whether the structure is long or short, and then substitutes the hair pixel.

- The restored hair pixel is then afterwards smoothed using the adaptive median filter.

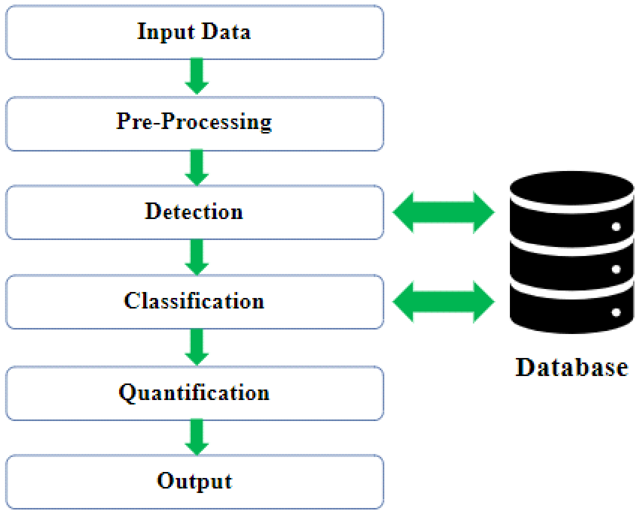


Figure 1: Pipeline of the proposed system

- **Image Preprocessing:** By increasing visibility, image enhancement tries to raise the quality of an image. Body hair frequently makes up the majority of skin lesions, making accurate and precise characterization challenging. As a result, the is eliminated from the photos using the dull razor technique. The following tasks are where the Dull Razor approach is most frequently applied:

- The hair on the skin strain is located using the grey scale segmentation method.

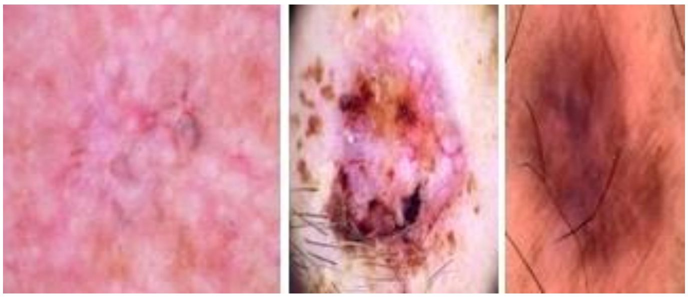
- The hair pixel is located, its length or thinness is determined, and it is subsequently exchanged via bilinear interpolation.

- An adaptive median filter is then used to smooth the recovered hair pixel. Augmentation ofimages.

- In order to effectively detect skin illnesses, skin depictions are changed and made simpler through image magnification. The training and assessment skin's image data sets were utilized to streamline the model and lower the likelihood of application errors. The add-on technology turns the skin image into RGB using scrolling, rotating, and cutting procedures as well as colour transformation to expand the library's storage space. To maintain the database's size and image quality for both healthy and unhealthy skin, moreskin photographs are upgraded.

- **Feature Extraction:** In order to provide the proper platform and suitable boundaries, the image processing feature must be removed. The extraction of vertical image-vectors can be done using a YOLOR[19]-based finding feature. The removal procedure assesses the structure, size, shape, colour, and other realistic aspects of the image database. This extraction method allows the different skin types to be correctly categorized. The moval technique eliminates the characteristics of diverse wound types and skin disease colours.

- **Skin-Based Classification:** The main objective of this research is to train a convolution neural network (CNN) to differentiate skin blight using a visual database. Two in-depth study approaches were employed to diagnose various disorders in skin cancer: It utilizes EfficientNet B0. The CNN classification model, which is based on an image processing system, employs trained and assessed skin image data to identify the skin cancer category.



actinic keratosis dermatofibroma melanomaFigure 2: Types of Skin Cancer

Using pre-trained EfficientNet B0 models, Figure 3 in this work shows images of early and late stage skin malignancies such actinic keratosis, basal cell carcinoma, dermatofibroma, and others.

In computer vision, object detection refers to the process of locating, classifying, and identifying one or more objects in a picture. To overcome this difficult issue, methods for object localization, object identification, and object categorization must be used.

To extract details about the objects and shapes in a photograph, significant processing of the same object detection and recognition on a computer is required. The identification of an object in an image or video is known as object detection in computer vision. For particular packages, a variety of ways has been employed to accurately and reliably identify the object. These suggested solutions are still ineffective and wrong, though. These object detection problems are better handled by deep neural networks and machine learning approaches.

In the area of computer vision, which has many applications, object detection has drawn a lot of interest. This includes automated management robots, the medical sector, leisure repute, agency security tracking, and more. Prior to anything else, well-known item identification techniques like the histogram of oriented gradients (hog) (hog) were discovered by using feature extraction techniques like the speed-up strong features (surf), adjacent binary, and adjacent binary. Both colour and style histograms (lbp) are used. The method of taking pictures and the equipment features that can describe a thing's attributes make up the main function extraction strategy.

A straightforward, practical, and successful unified object recognition paradigm for full-length images. In vacant regions, which are employed in programs that depend on swift, precise object recognition, YOLO also performed well. In a degenerative display that identifies degraded photos like noisy and occluded images, the model is trained on deteriorated photographs.

Due to its connections to video analysis and picture interpretation, object detection has recently attracted a lot of study attention. The conventional approach to object detection is based on handcrafted attributes and shallow trainable structures. Combining a range of low-level image features with high-level information from object detectors and scene classifiers is a straightforward technique to enhance the performance of object detectors and scene classifiers.

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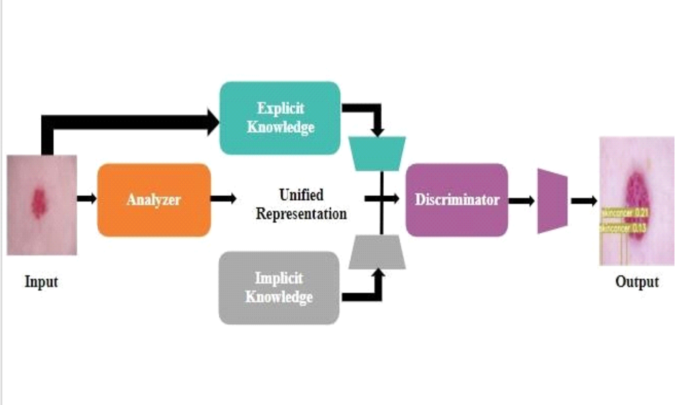

Figure 3:YOLOR model

- **EfficientNet B0 Architecture:**

EfficientNet Bo: Among the models utilized were Xception, InceptionResNetV2, and EfficientNetB0. The selected models obtained high Top-1 accuracy on the ImageNet dataset. They all employed categorical cross-entropy and the Adam optimizer for the loss function.

The second approach combined Sigmoid-only with InceptionResNetV2, Xception, and EfficientNetB3. During the training process, each model created a checkpoint of itself, documenting whether or not its balance was accurate at each epoch. The average balance accuracy of the chosen model checkpoints was used to gauge the effectiveness of the strategy. All models containing Sigmoid activation in their prediction layers were evaluated using the F1-score. Random cut, rotation, and flipping were used to improve the training set. Random cut, rotation, and flipping were also used to improve the training set.

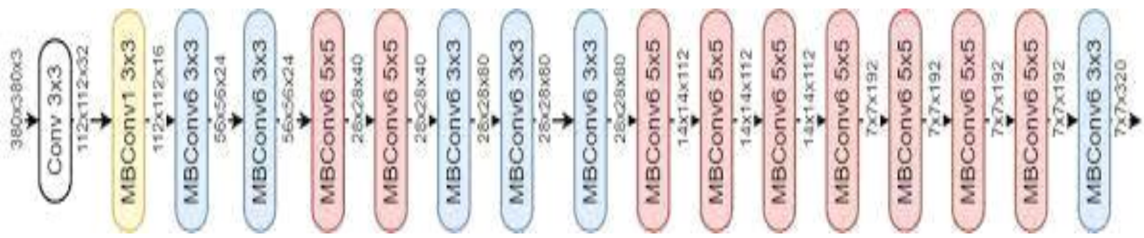

Figure 4: EfficientnetB0 Model

Model	*ImageSize*	*Epoch*	*Batchsize*
YoloR	416 *416	300	8
ficientNetB0	224*224	100	32

Table 2 lists the various training parameters that were usedto develop the different model classes.

Table 2: Training ParametersRESULTS AND DISCUSSION

Detection and Classification: The YOLOR model receives images of the troublesome area and uses them to determine whether or not the skin is cancerous. If the skin is malignant, the affected area is represented by a rectangle box.

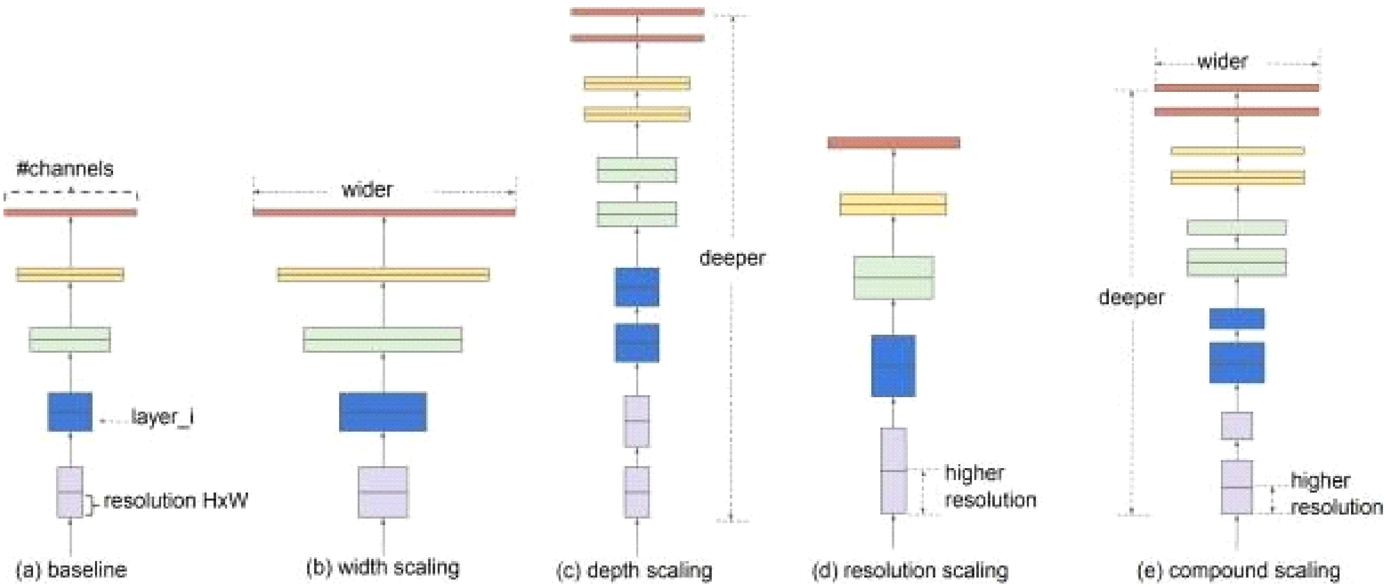

Figure 5:Prediction result of test image for Detection andClassification

Quantification: When a skin cancer image is discovered, the detection algorithm examines it and generates a heat map that shows the overall proportion of the affected skinregion.

CONCLUSION

YOLOR performs better than YOLOv4, Scaled YOLOv4, and earlier iterations. Feature alignment, multitasking, and prediction improvement are all included in the object detection functionality. The bounding box, confidence score, and class to which the object belongs are all included in this model's output. More potent methods for learning semantic, high-level, and deeper features are becoming available as deep learning develops, allowing it to address the shortcomings of conventional architectures. These models display a wide diversity of behaviors in terms of network architecture, training procedures, optimization strategies, and other factors. This study examines frameworks for deep learning-based object detection. In other words, this technique significantly increases the machine's accuracy in object recognition.

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