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Identification and Systematization of Skin diseases Using YOLOR

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Abstract: Skin disease, one of the deadliest types of cancer is becoming more lethal as fewer people become aware of its symptoms and how to prevent it. The purpose of this research is to identify and classify using machine learning and image processing techniques to treat various types of skin cancer. In this effort, we created a pre-processing image. We modified the dataset, reduced the size of the images, and removed hairs from them in order to meet the requirements of each model. Using pre-trained ImageNet weights and tweaked convolution neural networks, the EfficientNet B0 skin ISIC dataset was trained.

***Index Terms* - Disease Detection, Image Processing ,YOLOR, EfficientNet B0, Quantification are all terms that appear in this paper**

Introduction

The sixth most prevalent cancer is skin cancer, which is on the rise throughout the world. Normally, cells make up tissues, which in turn make the skin. Therefore, aberrant or uncontrollable cell growth in associated tissues or other neighbouring tissues is what leads to cancer. The development of cancer may be influenced by a number of variables, including UV radiation exposure, a compromised immune system, a family history of the disease, and others. Both benign and malignant cell growth patterns of this kind can occur. Cancerous growths known as benign tumours are frequently mistaken for unimportant moles. On the other hand, malignant tumours are managed like a cancer that may be fatal. . They may also harm the body's other tissues. The three types of cells that make up the skin's outer layer are basal cells, squamous cells, and melanocytes. These are to blame for the cancerous development of tissues. Melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC) are the three lethal types of skin disease (SCC).
Some examples of additional forms include vascular lesions, actinic keratosis (AK), benign keratosis, dermatofibroma, and melanocytic nevus.. Because it can return even after removal, melanoma is the most dangerous type of cancer.. The highest rates of skin cancer are found in Australia and the United States.

I. RELATED WORK

Yolo techniques based on DCNNs that are used to detect melanoma are described in the study by YaliNie& team, Automatic Melanoma Yolo Deep Convolution Neural Networks for Detection" [1]. They offer significant benefits for melanoma detection in lightweight system applications. With only 200 training photos, YOLO's mean average precision (mAP) can approach 0.82.
Another paper published by Hasna Fadhilah Hasya & team is A Convolution Neural Network and YOLO-based Real-Time Skin Cancer Detection System. The author of this paper [2] developed a system for detecting skin cancer in real time to assist patients who do not want to wait for hospital lab results. The objective is to develop an algorithm which can detect skin cancer which can simplify and improve clinicians' analysis of skin cancer results. YOLO is the real-time system, and the Convolution Neural Network (CNN) is used to process and group skin cancer image data. The overall accuracy of YOLOV3 is 96%, and the real-time accuracy
Early Melanoma Detection Performance Evaluation The Skin Lesion Classification System is one of the techniques that employs the MVSM classifier, according to the research of R.S. ShiyamSundar and M. Vadivel [3]. The most widespread type of skin disease is melanoma. The most effective way to reduce the disease's impact is to detect it early. The proposed technique classifies and considers five types of skin lesions: actinic keratosis, squamous cell cancer, basal cell cancer, and seborrheic verruca.
In their paper " A tool for annotating dermoscopy datasets " [5], Ferreira, P. M. present a basic idea for an annotation tool that can enhance Under dermatologist supervision, develop a ground truth image to use manual segmentation techniques to automate segmentation and classification processes. The feature extraction stage of any detection system is crucial. Among the primary features of this tool are a posteriori boundary edition, region labelling, segmentation comparison, border reshaping, multi-user ground truth annotation, manual segmentation, and image uploading and presentation.

Vedantin Chintawar and Jignyasa Sanghavi analyse numerous feature extraction strategies and suggest the most effective strategy for applications involving the detection of skin cancer in their study " Improving Skin Disease Diagnosis System Feature Selection Capabilities" [6]. The method of hair removal is the first and most important stage, followed by segmentation using the OTSU process. The projected system retrieves attributes such as wholeness, luminosity, fast corners, solidity, form skewness, and border skewness.

According to Hutokshi Sui, " Extraction of texture features for melanoma "[7], Specific characteristics must be. In this study, greyscale photographs rather than colour profiles are used to analyse the texture of skin lesions. In order to distinguish between various forms of skin cancer, SVM is employed as a classifier, and GLCM is used for feature extraction.

II. MATERIALS AND METHODS

A. DATASET

We used a custom dataset with 3000 images from Google Images and skin cancer samples in this paper..

Table 1 : Distribution of Dataset images

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***

IV.METHODOLOGY

The "You Only Learn One Representation" machine learning software has evolved into YOLOR. Modern object identification machine learning techniques like YOLOR have different authorship, design, and model architecture from earlier versions.

It is referred to as a "unified network for concurrently encoding implicit and explicit information" by YOLOR. The findings corroborate those of the YOLOR study article "You Only Learn One Representation: Unified Network for Multiple Tasks," which emphasise the importance of using implicit knowledge.

Figure 1 displays a functional diagram used to illustrate the suggested technique. Below are detailed explanations of each block.

Input Image: The ISIC 2019 Challenge data set, which consists of 9 classes, serves as the foundation for the suggested technique, each with eight photos. The proposed system was developed by academics at the University of Bristol using a dataset of high-resolution dermoscopic images.

Pre-processing: The technique utilised 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 the following step. The primary pre-processing procedures are noise reduction, image enhancement, 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.

Image enhancement attempts to improve the quality of an image by making it more visible. Body hair typically constitutes the majority of skin lesions, making accurate and precise classification difficult.

As a result, unwanted hair from pictures is removed using the dull razor technique. The Dull Razor method is most commonly acclimated complete the following tasks: a) The hair on the skin lesion is the grayscale morphological operation was used to locate. b) It locates the hair pixel, checks to see if the structure is long or thin, and then replaces the utilising bilinear interpolation, create hair pixels. c) Finally, the adaptive median filter is used to smooth the replaced hair pixel.

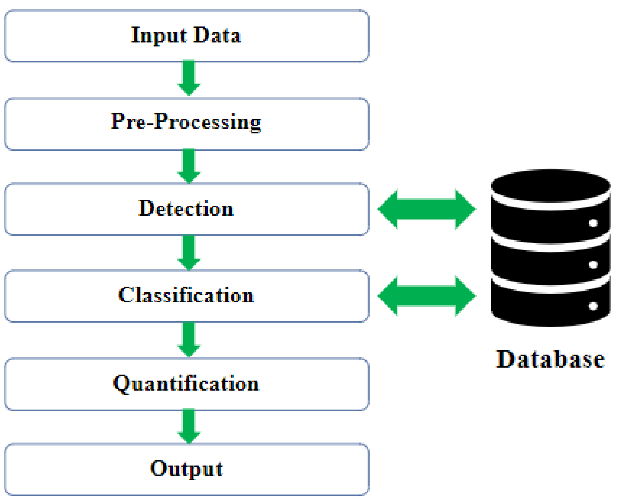

Figure 1: Pipeline of the proposed system

A. Image Pre-processing

Image enhancement aims to improve an image's quality by making it more visible. The majority of skin lesions are often composed of body hair, making accurate and precise definition difficult. As a result, using the dull razor technique, the is removed from the images. The Dull Razor method is most commonly used for the following tasks: a). The grey scale segmentation method is used to locate the hair on the skin strain. b) It locates the hair pixel, determines whether the structure is long or thin, and then replaces it with bilinear interpolation. b) The restored hair pixel is then smoothed using an adaptive median filter. Image Augmentation.

Image enlargement is used to change and simplify skin depiction in order to diagnose skin illness accurately. The image data sets of the training and evaluation skin were used to reduce the risk of misapplication and simplify the model. To increase the capacity of the skin image library, the add-on technique converts the skin image into RGB using scrolling, rotating, and cutting techniques, as well as colour transformation. More skin images, on the other hand, are enhanced to maintain the database's size and image quality for both healthy and unhealthy skin.

B. Feature Extraction

The removal of the image processing feature is critical in providing the right platform and appropriate boundaries. A YOLOR[19]-based discovery feature can be used to extract vertical image-vectors. The removal process evaluates the realistic qualities of image-database, which include colour, size, and shape, as well as structure. As a result of this extraction technique, the various skin types may be properly classified. There moval process removes the features of various wound forms and colors of these skin disease**.**

C. Skin-based Classification

The primary goal of this project is to use a visual database to train a convolution neural network to differentiate skin blight (CNN). To diagnose various diseases in skin cancer, two in-depth study methods were used: EfficientNet B0 is used. To classify the Skin cancer category, the CNN classified model based on the image processing system uses trained and evaluated skin image data..

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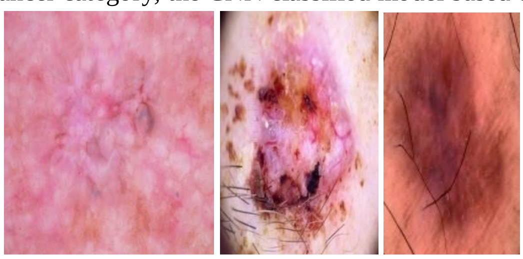


actinic keratosis dermatofibroma melanoma

Figure 2: Types of Skin Cancer

Figure 3 in this paper depicts images of early and late stage skin cancers such as actinic keratosis, basal cell carcinoma, dermatofibroma, and others using pre-trained EfficientNet B0 models.

Identifying one or more items in a picture and determining their presence, location, and kind is known as object detection in computer vision. Techniques for object localization, object identification, and object categorization must be applied to resolve this challenging problem.

The same object detection and recognition on a computer must be processed extensively to extract information about the items and shapes in a picture. Object detection in computer vision is the detection of an object in an image or video. To precisely and reliably identify the object, various methods had been used for specific packages. However, these proposed alternatives are still inefficient and inaccurate. Deep neural networks and machine learning techniques are more effective at dealing with these object detection issues.

Object detection has received a great deal of attention in the field of computer vision, which is used in a variety of applications. The medical industry, leisure reputation, agency security tracking, and automated management robots are all covered. Prior to anything else, feature extraction techniques such as the histogram of oriented gradients (hog), speed-up strong features (surf), and adjacent binary were used to discover well-known item identification methods such as the histogram of oriented gradients (hog) (hog). Color histograms as well as styles (lbp). The primary function extraction strategy is the method of shooting images and the equipment features that can characterise the properties of things.

A unified object identification model that is simple, usable, and works well with full-length photos. YOLO also performed well in unoccupied areas, which are used in programmes that rely on quick, accurate object identification. The model is trained on deteriorated photographs in a degenerative exhibition that identifies degraded images such as noisy and occluded images.

Object detection has recently received a lot of research attention due to its close ties to video analysis and image interpretation. The traditional method of object detection is based on shallow trainable structures and handcrafted characteristics. A simple way to improve the performance of object detectors and scene classifiers is to combine a variety of low-level image attributes with high-level context from object detectors and scene classifiers.

YOLOR, as opposed to other machine learning use cases such as object analysis or identification, is specifically designed for object detection. This is due to the fact that object detection relies on broad identifiers to assign an object to a specific class or category. Other machine learning applications, on the other hand, necessitate more precise procedures. To identify items, the machine learning model must be sensitive to the various details that distinguish them from one another.

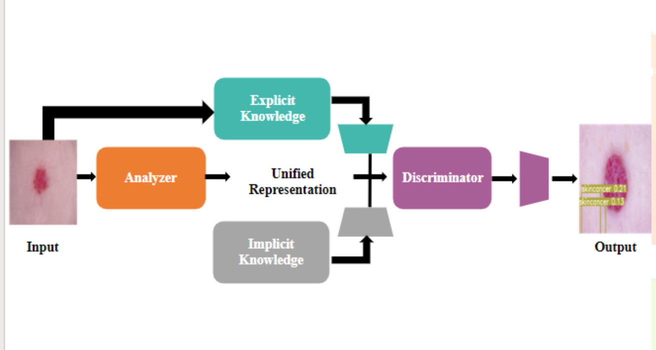


Figure 3:YOLOR model

A. EfficientNet B0 Architecture

EfficientNetB0:Xception, InceptionResNetV2, and EfficientNetB0 were among the models used. On the ImageNet dataset, the chosen models achieved high Top-1 accuracy. For the loss function, they all used categorical cross-entropy and the Adam optimizer.

The second method used InceptionResNetV2, Xception, and EfficientNetB3 in addition to Sigmoid-only. Each model built a checkpoint of itself during the training process, recording whether or not its balance was accurate at each epoch. The technique's performance was assessed using the average balance accuracy of the selected model checkpoints. The F1-score was used as an evaluation criterion for all models with Sigmoid activation in their prediction layers. To enhance the training set, random cut, rotation, and flipping were employed. To enhance the training set, random cut, rotation, and flipping were also employed.

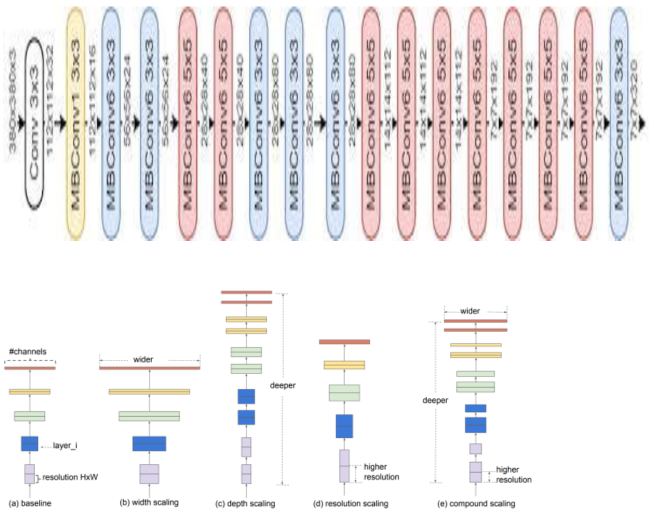


Figure 4: EfficientnetB0 Model

The various training parameters utilised to train the various model classes are displayed in Table 2.

TABLE 2:Training Parameters

Model	*Image Size*	*Epoch*	*Batch size*
YoloR	416 *416	300	8
EfficientNet B0	224*224	100	32

V. RESULTS AND DISCUSSION

Detection and Classification: Images of the problematic area are sent to the YOLOR model, which assists in identifying whether or not the skin is malignant. A rectangular box is used to symbolise the afflicted area if the skin is malignant.

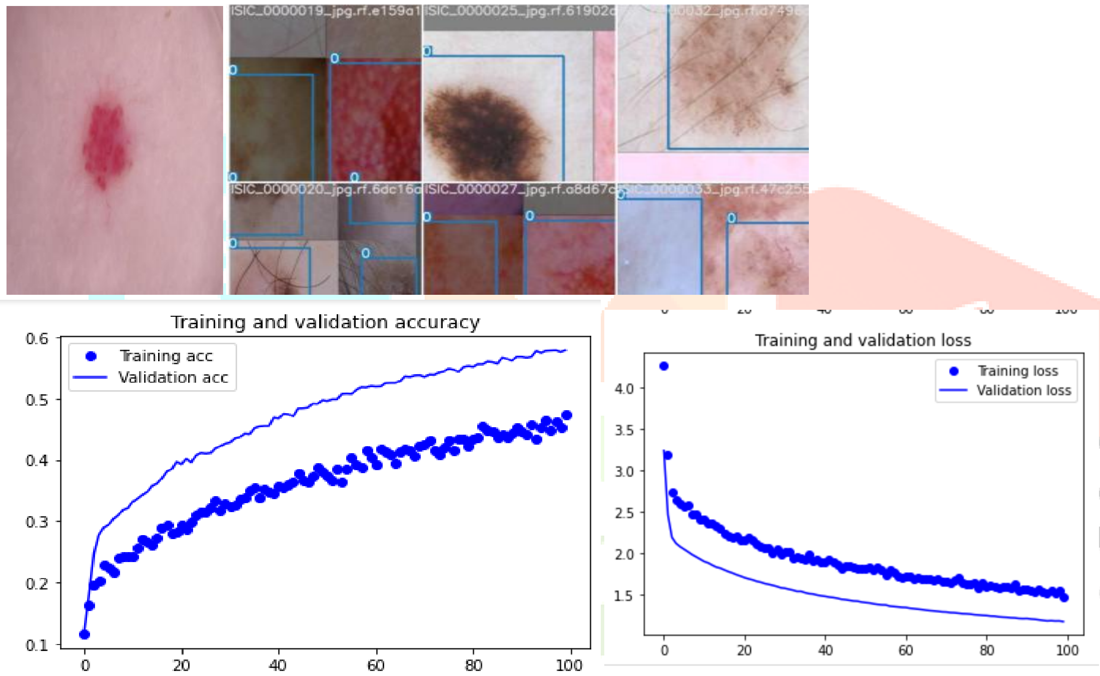
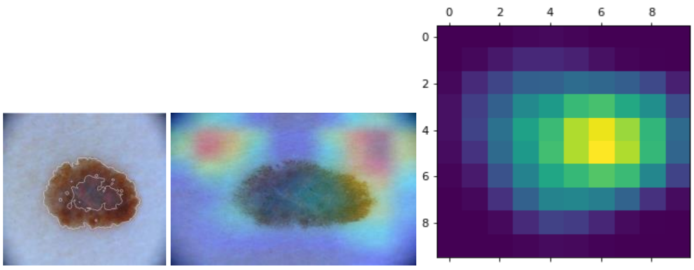


Figure 5:Prediction resultoftestimage for Detection and Classification

Quantification: The detection algorithm analyses a skin cancer image when one is found, and creates a heat map that displays the overall proportion of the diseased skin region.



VI. CONCLUSION

YOLOR outperforms the YOLOv4, Scaled YOLOv4, and previous versions. The object detection functionality includes feature alignment, multitasking, and prediction refining. This model's output includes the item's bounding box, confidence score, and the class to which the object belongs. As deep learning advances, more powerful tools for learning semantic, high-level, and deeper features are becoming available to address the issues with traditional architectures. In terms of network architecture, training methods, optimization techniques, and so on, these models exhibit a wide range of behaviors. This research looks into deep learning-based object detection frameworks. In other words, this method greatly improves the machine's ability to recognize objects accurately.

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