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ENHANCED HISTOGRAM INTEGRATED MORPHOLOGICAL IMAGE QUALITY ENHANCEMENT MODEL USING DERMOSCOPY IMAGES WITH EDGE BASED SEGMENTATION

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ABSTRACT

Melanoma is a major type of skin cancer, and its accurate and prompt identification is becoming more and more important every day. The development of state-of-the-art models and computer vision methods has made analysis much simpler. Effective skin cancer segmentation and classification methods necessitate well-defined lesions isolated from their surroundings. One typical method for detecting edges is to employ a two-dimensional filter that is trained to rely on big gradients to identify changes in pixel intensity in a scene. The operator is subsequently employed to convolve the picture. Edge detectors accumulate many images and apply a local image processing method to identify sudden changes in an intensity function. There have been a plethora of new proposals for pre-processing skin lesions that aim to assist segmentation algorithms in producing good results. More and more people are losing their lives to melanoma each year. Stage I melanoma diagnosis, on the other hand, are associated with better survival chances. The process of melanoma segmentation is quite laborious since it must take into account both the top and bottom of the tumor. We apply a new approach to improving and segmenting melanoma images. Low contrast in dermoscopy images of the skin is often caused by lighting conditions that vary. Because dermoscopy images of melanoma have low contrast, the lesion tends to blend in with the surrounding skin. In addition, the low contrast makes it difficult to make out a number of visual elements. Because of this, there has to be a way to make dermoscopy pictures more detailed and contrasty. To mitigate the effects of low contrast and improve image quality, a morphological method is proposed in this research. A localized set of both light and dark features can be retrieved from a image using image reconstruction. By removing the dark elements and adding the nearby bright ones, the image quality can be improved. This research presents a Enhanced Histogram Integrated Morphological Image Quality Enhancement Model using Dermoscopy Images with Edge based Segmentation (EHIMIQE-DIES). The proposed model performs feature extraction from the quality images. The proposed model is compared with the traditional methods and the results represent that the proposed model performance is high in image quality enhancement and in segmentation.

Keywords: *Enhanced Histogram, Morphological, Dermoscopy Images, Segmentation, Edge Detection, Image Quality, Feature Extraction.*

1. INTRODUCTION

Tumors form when human skin cells divide and grow unevenly; melanoma, squamous cell carcinoma, and basal cell carcinoma are the three main types of skin cancer. Predicting the incidence of skin cancer, according to the World Health Organization (WHO) data, is 37.2 percent [1]. The fact that half of the 24 million instances of cancer reported globally in 2023 were fatal lends credence to the severity of this disease. Melanoma originated in melanocytes and is a kind of skin cancer that grows quickly and is very dangerous [2]. Melanocytes serve primarily as cells that produce melanin; they are highly specialized. This process of differentiation drastically reduces the cell's proliferative capacity [3]. Observing the lesion's shape, size manually is the gold standard for examining skin lesions. Because professionals and dermatologists need to physically perform these

operations, they are less precise and take more time. It is crucial to prioritize the early detection for skin cancer in order to control its fatality rate [4]. Artificial intelligence models, on the other hand, are gradually settling these differences. New computer-vision-based deep & machine learning algorithms have been introduced in the previous few years. These cutting-edge methods allow medical professionals to detect and categorize these diseases with the help of a machine. Hence, for better accuracy and efficacious outcomes, a computer-aided prognosis is necessary [5].

Melanoma detection control approaches strive to improve diagnostic accuracy by reducing needless variability. Consistency in diagnostic processes and the integration of modern techniques alongside traditional approaches are the main goals of these controls. When it comes to diagnosing melanoma, dermoscopy is considered to be the gold standard. It makes it possible to visually check skin lesions in great detail, which improves the detection of cancerous features and decreases the subjectivity associated with visual inspection.

Malignant melanoma ranks high among the skin cancers that cause the greatest number of deaths worldwide. The likelihood of metastases is reduced with early detection [6]. Dermoscopy technology facilitates the detection of skin cancers and the diagnosis of melanoma. Automated image processing techniques for dermoscopy pictures are now essential for the identification of skin lesions. The fundamental elements of these approaches are picture acquisition, lesion border detection and segmentation, feature extraction, and classification [7]. The dermoscopy picture segmentation and detection technologies utilized in the subsequent stages significantly impact the efficiency of early skin cancer identification.

The introduction of CAD systems is aimed at enhancing the accuracy and speed of melanoma diagnosis [8]. In order to identify melanoma skin cancer, computer-aided design systems extract the lesion or lesions from the skin image. Unfortunately, the most effective algorithms for segmenting skin lesions in pictures with artifacts like hairs and corner borders are not yet available, which means that CAD systems' melanoma diagnostic accuracy falls short of expectations. The melanoma and benign images are shown in Figure 1.

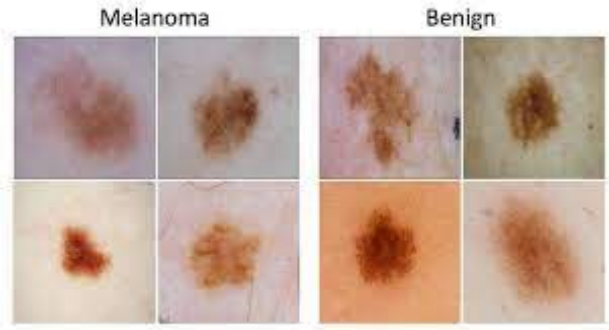

Fig 1: Melanoma and Benign Images

A feature of skin cancer is the abnormal proliferation of specific cells on the dermal layer, which is caused by alterations in gene expression [9]. Nearby cells were infiltrated by these cancerous cells. The human body is vulnerable to several factors, such as increased life expectancy and exposure to ultraviolet radiation, which has led to a huge number of cancer patients emerging in the modern period [10]. Malignant and benign skin cancers are the two most common types. What differentiates the two categories is the ability to metastasize, or spread to different parts of the body. The most deadly cancers have the potential to metastasize, or spread to other organs and eventually kill the patient. Lymphatic and circulatory systems allow it to potentially reach faraway organs and tissues [11]. Most people will be affected by this condition at some point. The environmental impacts of benign cancer can still occur if it presses on neighboring neurons or blood vessels, even though it is little. In general, benign malignancies progress more slowly than malignant ones. Negative effects on the human body may occur from cancers that are not treated effectively [12]. Preliminary testing is crucial for accurately diagnosing skin cancer [13]. As part of this procedure, a biopsy is performed, which is invasive and painful for cancer patients. Dermoscopy imaging aims to avoid unnecessary biopsies by providing a detailed examination of the skin layers using a microscope and other specialized illumination equipment [14].

Determining the nature of the skin lesion and verifying its existence in dermoscopy pictures is the primary obstacle. There are only a few of steps required to detect skin lesions, including segmentation, feature extraction [15], and classification [16]. This research presents an automatic segmentation method as an initial step towards skin lesion classification. Because it can detect skin cancer by recognizing and localizing the locations of skin lesions, this automated method is

very useful for dermatologists. Clinicians typically use visual inspection as a screening tool for skin cancer. Clinicians search for moles and other spots that differ in color from normal skin during cancer screenings [17]. Dermatologists cannot promise a 100% success rate in visually screening for skin cancer, and there are cases where it could even cause harm [18]. Unnecessary operations can cause injury, such as skin biopsies for lesions that were not cancerous or that were undetected and should not have been biopsied, which can lead to death. Even for highly trained dermatologists, the visual examination only yields a 60% diagnosis accuracy rate. Consequently, skin lesion analysis tools that can automatically diagnose skin cancer and provide a high level of accuracy are clearly needed [19].

Morphology refers to a wide category of image processing techniques that analyze images according to their shapes [20]. By applying a structural element to an input image, morphological procedures generate an identically sized output image. Some basic operations depending on the shape of the image are morphological transformations. This operation is typically carried out on binary images [21]. The initial image is one of the two inputs; the second is a structural element, sometimes known as a kernel, that determines the operation's kind. The morphological operators erosion and dilation are two fundamental ones. Histogram equalization is a method for improving images. To improve contrast, histogram equalization is used to change image intensities [22]. When the image's useful data is represented by close contrast values, this strategy typically boosts the global contrast of dermoscopy images [23].

Segmentation, feature extraction, and classification form the backbone of an automated diagnostic tool for skin lesion analysis [24]. Given that subsequent tasks are dependent on accurate segmentation, it is clear that segmentation is the most crucial of these three activities. The shape, size, borders, and color of lesions varied substantially between skin types and textures, making lesion segmentation a challenging task. In addition to these differences, the lesion borders are uneven, and the transition between the lesion and skin is extremely smooth, making it extremely difficult to distinguish between normal skin and a lesion. It is difficult to segment dermoscopic images because of the presence of artifacts like as hair, pen traces, air bubbles, and so on. An essential first step in the process of detecting and classifying lesions from recorded pictures is lesion extraction [25]. Experts have previously devised a number of lesion extraction methodologies to aid in the efficient identification and classification of lesions utilizing computer-vision-assisted diagnostic systems. Lesson extraction from dermoscopy images is still a challenging task due to the fact that lesions vary in size, color, shape, and position on the human body, as well as in contrast within lesion boundary regions. This makes the process computationally intensive and leads to erroneous lesion extraction. In response to these issues, numerous supervised, unsupervised, and deep learning techniques have been created to improve the accuracy of lesion extraction. The image segmentation on melanoma image is shown in Figure 2.

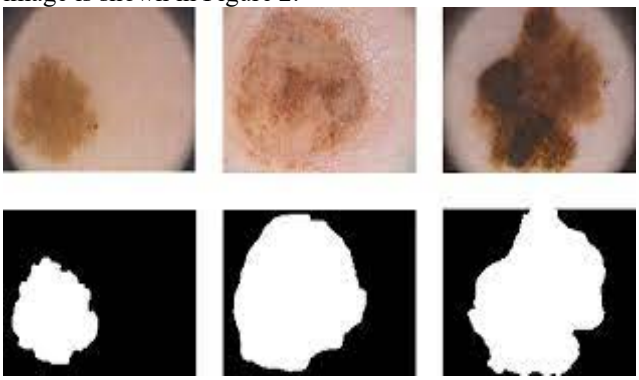

Fig 2: Segmented Images

When working with digital images, edge detection is a common technique. One way to find sharp edges in a image is to use an edge detection algorithm. Rapid changes in pixel intensity define the boundaries of objects in a scene, and these changes are known as the boundaries for object surfaces discontinuities [26]. An image edges are the shapes that emerge from the abrupt alteration of numerous properties at the pixel level. A change in color, texture, shade, or light absorption could cause these changes to be noticeable. Size, orientation, depth, and surface feature estimation in images could be advanced by these traits. Computerized Tomography (CT), Position Emission Tomography (PET), and Magnetic Resonance Imaging (MRI) scans have all made heavy use of edge detection to spot structures and abnormalities in medical pictures. Since an edge is a composite of high-frequency data, the detected images contain high-frequency noise or irrelevant data, which prevents the recognition of continuous edge points. A wide variety of approaches combine region-growing and edge-detecting algorithms to accomplish image segmentation and edge-detecting jobs. In order to identify gray matter structure, for instance, it uses intensity threshold methods, region

selection, and multi-resolution edge detection to identify regions to grow, and it combines special as well as intensity information in an image segmentation approach. In order to take local differences in image intensity into consideration, algorithms are expanding their scope to incorporate spatial limitations. This research presents a Enhanced Histogram Integrated Morphological Image Quality Enhancement Model using Dermoscopy Images with Edge based Segmentation.

2. LITERATURE SURVEY

Riaz et al. [1] provide a computer-assisted diagnostic method for melanoma detection in dermoscopy images. Clinical research has shown that melanoma lesions are characterized by a pigment network and streaks rather than smooth boundaries, distinguishing them from normal skin patches. The author validated these findings by first segmenting the skin lesions and then extracting the lesion's outside area. In order to identify melanoma, this region will thereafter be utilized for feature extraction and lesion classification. Beginning with the lesion's contour, the new active contours based segmentation method fits a curve to the lesion's boundaries by utilizing the skin's and lesion's Kullback-Leibler divergence. Melanoma can be detected by extracting the perimeter of a lesion using image characteristics generated from local binary patterns. This process is done after lesion segmentation. These methods were tested on the publicly accessible PH 2 and ISIC dermoscopy datasets. Experimental research has shown that the outside edges of melanoma lesions contain the most important characteristics, and that the proposed segmentation method agrees with the ground truth data.

Dermatologists frequently use follow-up dermoscopy pictures of image lesions to confirm a diagnosis or rule out early-stage melanoma. On the other hand, current algorithms for early cancer diagnosis rely on images of lesions taken at a single time point. In borderline circumstances, a mistake may occur if the morphological and temporal alterations of lesions are disregarded. Here, Yu et al. [2] presented a methodology for automated sequential dermoscopy-based early melanoma detection. Therefore, this system is built in three stages to achieve this goal. Before proposing a spatio-temporal network to capture dermoscopic modifications between aligned lesion images and the associated difference images, the author aligned sequential dermoscopic images for lesions on the skin using estimated Euclidean transformations. The author then used image differences to extract the lesion growth region. The final product is an early diagnosis module that uses evolutionary lesion image data to calculate probability scores of malignancy. The 179 serial dermoscopy images from 122 patients served as the basis for this method's verification. The suggested model beats other popular sequence models, according on the results of the extensive testing. Seven seasoned dermatologists & five registrars were also included in the comparison of this model's diagnostic outcomes.

Without prompt diagnosis and treatment, skin cancer has the potential to spread to other parts of the body, making it one of the most deadly forms of cancer. Applying deep learning to skin cancer has been a game-changer in health care in recent years, and dermoscopy images have been at the center of this technological revolution. Recent advances in dermoscopy-based automatic skin cancer diagnosis based on deep learning were examined by Nie et al. [3]. Deep learning's present status and its possible applications in dermoscopy image diagnosis are explored extensively in this paper. The main objective of this study is to present a synopsis of the existing methods for melanoma categorization along with suggestions for how to improve them. The author took into account current advances in deep learning-based approaches for skin cancer diagnosis, some challenges, and possible future improvements to these automated systems in order to better aid dermatologists in their work.

An important part of early diagnosis and prognosis for many skin diseases is skin lesion segmentation using dermoscopy pictures. The wide variety of lesions of the skin and the haziness of their borders make this an uphill battle. And while there are some skin lesion datasets out there, the vast majority are more suited for disease classification and have far fewer segmentation labels. Wang [4] presented autoSMIM, a new approach to skin lesion segmentation using automated super pixel-based masked image modelling in a self-supervised environment, to solve these problems. It processes a large number of dermoscopy images without labels in order to discover implicit visual features. The first step of autoSMIM is to restore an input image that has super pixels that have been arbitrarily masked. Next, a new proxy task is implemented using Bayesian Optimization to update the policy of creating and hiding superpixels. A fresh masked

image modeling model is trained using the best policy. The downstream segmentation of skin lesions job is then used to fine-tune the model. Three segmentation of skin lesions datasets, namely ISIC 2016, ISIC 2017, and ISIC 2018, are subjected to extensive experimentation. Research on laser ablation has proven that autoSMIM is flexible and that masked image modeling based on super pixels is successful.

It is crucial to segment medical images for accurate diagnosis and treatment planning. Methods determined by CNNs, particularly U-Net and its derivatives, have demonstrated outstanding performance on medical image tasks related to segmentation in the past several years. However, images with complex architecture and a broad variety of ROIs don't always yield solid results. This could be due to the fixed geometric configuration of the extraction of features receptive fields or the information-loss effects of repetitive down-sampling processes. To solve the data contraction and semantic gap issues, as well as to get multiple scales setting features with different receptive fields, Alam et al. [5] replaced the convolution block with a dilated convolution block and add a dilated beginning block between the decoder and encoder routes to the standard U-Net architecture. This adjustment aids in getting past these issues. In addition to re-weighting its channel-wise information responses to enhance feature representation overall, a squeeze & excitation unit fixes the problem of vanishing gradients by adding the input for every dilation convolution blocks to the output.

Automated skin tumor diagnosis relies heavily on lesion recognition in dermoscopy images. Since this task necessitates a substantial amount of medical knowledge, the medical perspective is vital, but most present solutions disregard it. While some approaches are based on medical knowledge, they don't necessarily align with how doctors learn and diagnose patients, as certain strategies and procedures in their profession are unique to doctors. In order to improve analysis, Liu et al. [6] proposed Clinical-Inspired Network (CI-Net) to incorporate doctors' learning strategies and diagnostic processes. The three primary steps of a diagnostic procedure are zooming in, watching, and comparing. In order to replicate them, the author presented a feature extraction module, an attention module for lesion areas, and an attention module for lesion features.

An accurate diagnosis and objective evaluation of port-wine stains (PWS) from medical photographs rely on automatic segmentation of these stains. This is a challenging task because of overall indistinguishability of PWS lesions, color fluctuation, and low contrast. These challenges are addressed by designed by Mu et al. [7]. The author proposed state-of-the-art multi-color spaces adaptive fusing network (M-CSAFN), which is highly effective at PWS segmentation. The first step is to build an multi-branch identification model with six standard color spaces. This model will use data on color texture to help distinguish between surrounding tissues and lesions. The second phase involves utilizing an adaptive fusing technique to integrate complementary predictions. This takes into account the large variances within the lesions caused by color heterogeneity. The author provided a color-aware evaluation of structural loss to put a number on the discrepancy between real and expected lesions. For the purpose of creating and evaluating PWS segmentation algorithms, a PWS clinical dataset was also set up, containing 1413 image pairings.

Many studies have looked into DCNN models for skin disease assessment, and some of these models have shown diagnostic results that are on par with or even better than dermatologists'. The publicly available skin lesion datasets are limited and data imbalanced, which hinders the broad deployment of DCNN in disease identification. On small and unbalanced data sets, Yao et al. [8] suggested a new single-model based approach for skin lesion categorization. In order to ensure that models of moderate complexity perform better than larger ones, a number of DCNNs undergo training on diverse imbalanced and small datasets. To address the issues of underrepresentation in the short dataset, a Modified RandAugment augment approach is suggested, and normalization DropOut and DropBlock are included to decrease overfitting. Lastly, an end-to-end cumulative learning strategy (CLS) and a new Multi-Weighted New Loss (MWNL) function are presented to address the problem of uneven sample size and classification difficulty, as well as to mitigate the effect of out-of-the-ordinary samples on training. Through the integration of Modified RandAugment, MWNL, and CLS, the single DCNN model outperformed or was on par with numerous ensembling models on various dermoscopy image datasets in terms of classification accuracy.

As a final result of the test, computer vision systems can provide digital outputs like a diagnostic indication and an uncertainty interval. Here, building on previous work on melanoma diseases, Mencattini et al. [9] presented an image analysis platform that makes use of variational automatic encoding (VAEs), a class of generative models in deep learning that learn to reproduce an image in output via an encoder/decoder. Latent variables (LVs) extracted using the VAE architecture provide concise representations of the appearance of image objects for the aim of phenotyping skin malignancies. In order to select more reliable indicators of malignant malignancy, the author presented state-of-the-art methods that use the propagating uncertainty via the VAE system, which is linked to skin tone fluctuation and gel bubble effects, as an index. The idea here is that the predicted fluctuation of a descriptor in relation to disturbances is a good measure of its discriminatory power. Using 500 photographs from the wider dataset of images from dermoscopy ISIC 2016-2017 which includes images of benign and malignant outcomes, respectively, the author addressed the issue for the binary classification of cancer evaluation in this work. The author proved general validity by comparing the results to those from a standard convolutional neural network, or CNN, based transfer learning method.

A senior public health concern, skin cancer could benefit from computer-aided diagnosis in the fight against this pervasive disease. The time wasted by visual examination has prompted researchers to focus on developing computer-aided diagnosis solutions. Skin lesion segmentation is the first step in skin lesion assessment and could be useful for the next classification task. The process becomes more challenging when the entire lesion appears to be the same hue and the boundaries of pigment areas become unclear. While skin lesion segmentation has been successfully addressed in a number of research models, there is still a need to create new approaches to enhance efficiency. Hosny et al. [10] examined state-of-the-art algorithms and techniques for segmenting skin lesions in great detail. The review starts with the more conventional methods of segmentation and then quickly moves on to discuss skin lesion segmentation with an emphasis on optimization and deep learning. Various algorithms' merits and shortcomings are emphasized in this study. It also looks at the metrics utilized to measure the success of these methods and different datasets that are typically used for skin lesions.

3. PROPOSED MODEL

Human visual factors, such as visual weariness, sometimes cause failure in the demarcation of the lesion, which hinders the first stage, which is important for a previous diagnosis and where the cure probability is greatest. In addition to being crucial for the subsequent steps of skin lesion extraction and classification, automatic area of interest segmentation is required to achieve a precise contour while decreasing the occurrence of errors. The processing of images is crucial because it allows for the early diagnosis of specific cases, which in turn leads to the possibility of a cure.

This type of skin cancer can now have a treatment plan defined with the use of digital image processing tools. Professionals in the industry will have no qualms about using this technology to quickly and confidently diagnose patients. More and more, industries are realizing the benefits of digital image processing for tasks that require ways to extract useful information from photos for human analysis. The prognosis for the condition improves when it is discovered or diagnosed early. Once a lesion has reached an advanced stage and penetrated the dermal layers, stopping its spread becomes nearly impossible. This is why skin cancer, which does not include melanoma, has a substantially higher mortality rate than other cancers [27]. Examining the lesions' asymmetry, border, color, and diameter as physical characteristics is the so-called ABCD rule that most melanoma diagnostic tests adhere to. For the simple reason that benign nevi and dots might be mistaken for melanoma, making early detection extremely challenging.

A dermatoscopic is a specialized tool that can estimate the likelihood of different types of skin cancer. Dermatoscopy is a noninvasive technique that uses a magnifying lens to study microscopic images of the skin's tissues and its surface characteristics. Since the dermatoscope shows the parameters of the ABCD rule, the operator's degree of skill and experience is a subjective but distinguishing factor in skin cancer classification from visual pictures. Screening for skin cancer begins with differentiating melanocyte lesions from non-melanocyte ones; next, the color and shape of the lesions are used to determine if they are benign, malignant, or cause for concern. In the first research on automated methods for skin cancer risk assessment, dermoscopy pictures were widely used [28].

In order for the dermoscopy skin cancer partition algorithm program to function, these images are necessary. Dermoscopy images, which typically have a larger distance between the skin and the lesion, are used by the majority of segmentation algorithms. In order to determine the status of the boundary lesion, the segmentation algorithmic software runs. One way to process images is by histogram equalization, which changes the intensity distribution of the histogram to change the contrast of the image. This method's goal is to have the image's cumulative probability function trend linearly. With M intensity levels ranging from 0 to (M-1), the histogram of a digital image can be expressed as h(rM) = nM, where rM is the Mth intensity level and nM is the number of pixels in the image that have that density. Dividing the histogram by the sum of all the pixels in the picture is another way to normalize it.

An image is considered white or bright if its histogram is skewed to the right. A low-contrast image with a few levels of grayscale is shown by a narrow-width histogram plot centred on the intensity axis. The opposite is true when the histogram is uniformly distributed over the whole x-axis, which results in a stunning display of contrast. Increasing the image's contrast is a common requirement in image processing. When this occurs, histogram equalization can be applied that is an intensity transformation method. By selecting an appropriate intensity transformation function, histogram equalization spreads the image histogram evenly throughout the whole intensity axis. Therefore, transforming intensities is what histogram equalization is all about.

Morphological filtering is used to eliminate noise from the images in the pre-processing step. This is necessary since the database is built from images acquired from various sources, such as bases with varying types of lighting, resolution, etc. Reconstructing or reducing the proportions of the undesirable spatial structures in the dermatoscopy images is an essential part of the suggested strategy. Lesions include one of the most common components that can damage any segmentation system. As part of the preparation phase, smoothing out the image is performed and noise is removed using morphological filtering, which is based on a Gaussian kernel. By enhancing the lesion's colors, morphological filtering hopes to draw attention to its geometry from the bottom up while preserving its shape and preventing distortion. The grayscale image undergoes median filtering, which employs a nonlinear function within the image to eliminate the pepper and salt noise.

This approach improves upon convolution operations in terms of efficiency, while simultaneously protecting image edges and reducing noise. To remove hairs and smooth the image against noise, a 2D median filter with a size of 20 x 20 and a morphological filter based on a Gaussian kernel were used. Two characteristics, similarity and discontinuity, are used to classify image segmentation algorithms. A edge based method is one that relies on discontinuities. By identifying areas or items within a image that share common attributes, segmentation can be used to categorize the image. A finite set of areas R1…Rn is mathematically complete for an image I. Most future tasks involving image analysis rely on image segmentation. The process of segmentation breaks a image down into its individual parts or objects. Simplifying or transforming an image's representation into something more relevant and easier to evaluate is the main objective of segmentation. Two fundamental features of intensity values discontinuity and similarity form the basis of the segmentation algorithms. One approach is to divide a image into several parts according to features with sharp contrasts, such its edges. The second type relies on dividing a image into similar areas based on a set of rules. The pre-processed images are segmented using edge based segmentation method in this research. The proposed model framework is shown in Figure 3.

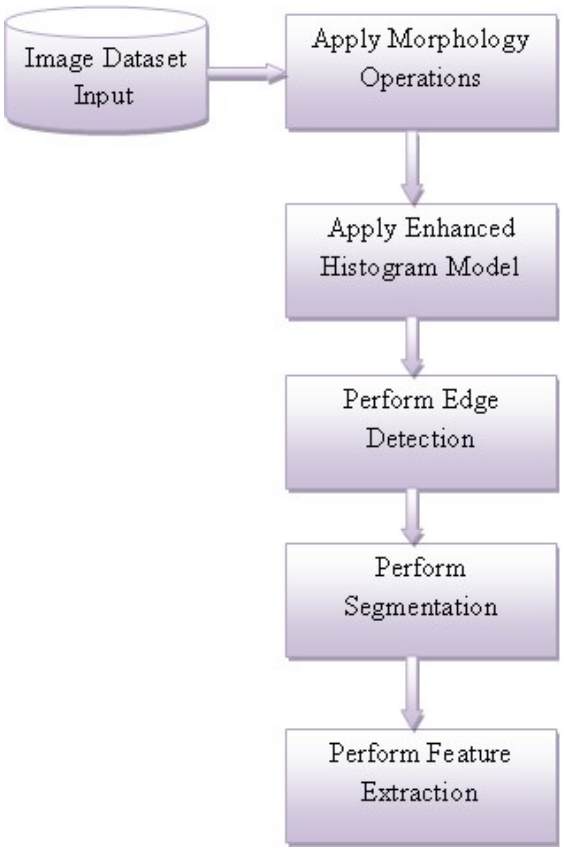

Fig 3: Proposed Model Framework

Segmentation, feature extraction, and classification form the backbone of an automated diagnostic tool for skin lesion analysis. Given that subsequent tasks are dependent on accurate segmentation, it is clear that segmentation is the most crucial of these three activities. The shape, size, borders, and color of lesions varied substantially between skin types and textures, making lesion segmentation a challenging task. In addition to these differences, the lesion borders are uneven, and the transition between the lesion and skin is extremely smooth, making it extremely difficult to distinguish between normal skin and a lesion. The segmentation procedure is further complicated by the presence of artifacts in dermoscopy images, which might include air bubbles, hair, pen traces, and more. This research presents a Enhanced Histogram Integrated Morphological Image Quality Enhancement Model using Dermoscopy Images with Edge based Segmentation. The proposed model performs feature extraction from the quality images.

Algorithm EHIMIQE-DIES

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Input: Image Dataset {IDset}

Output: Extracted Feature Set {EFset}

Step-1: Initially, the images are considered from the dataset and the images undergo morphology operations to improve the quality of the images. By applying a structural element to an input image, morphological procedures generate an identically sized output image. Each pixel's value in the final image is determined by morphological operations, which compare each pixel in the input image to its neighbors.

The morphological operations include erosion and dilation to improve the image quality. Erosion can reduce the size of the image's pixels or even eliminate them entirely from the edges of an item. In order to execute an erosion operation on the image object, the structuring element is moved first across it. Pixels in a image are enlarged or border pixels are added by dilation. Before performing a dilation operation on the image object, the structuring element is iteratively traversed. A structuring set B, also known as the structuring element, interacts with an image A, the object of interest, to undergo certain alterations.

While any form will do for the structural element B, a circular disc in the plane is the most common. Sets in the two-dimensional plane are not necessary for the image and structural element sets.

Assume that A and B are subsets of Z^2.

A_x is the notation for the translation of A by x, and it is defined as

$$(A \ominus B)[M] = \sum_{i=1}^{M} \{z \in E | B_z \subseteq \mathbf{A}\}$$

$$Eros[M] = \bigcup_{i=1}^{M} (A \ominus B)_x + \{z \subset \mathrm{E}\}$$

Dilation of image A by structuring element B is considered as

$$(A \oplus B)[M] = \sum_{i=1}^{M} \{x: B_x \cap A \neq \emptyset\}$$

$$Dila[M] = \bigcup_{i=1}^{M} \bigcup_{b \in B}^{M} B_x + \{z \subset \mathrm{E}\}$$

Step-2: To reduce the issues of saturation artefacts, change in mean brightness, and over-enhancement that arise with traditional histogram equalization, a regulated contrast method based on an enhanced

histogram was created. The first step is to use the median of the input image to split the histogram into four smaller ones. Splitting the histogram in half allows it to equalize each sub-histogram independently. The boosting effect is improved while processing time is reduced by doing the dividing technique only once. To guarantee correct pixel distribution, the features of the histogram are carefully examined before deciding on the segmentation point.

The histogram is defined as the set of all pixels P_x with an intensity level between 0 and 1 and a half (Im-1) that is calculated as

$$HE(i*j)=\sum_{i=1}^{M} kj$$

where ij are the k^{th} intensity level and ij is represents the pixels count with the specified levels. Dividing the histogram by the sum of all the pixels in the image is another way to normalize it. An enhanced histogram function is defined as

$$EHE[M]=\sum_{i=1}^{M}\sqrt{\frac{getimg\left(HE(i,i+1)\right)}{M-i}+getpixrange(p,q)+\frac{HE(i+1)}{HE(i)}}+\lambda(i,i+1)$$

Where λ is the model for considering the poor intensity pixels.

Step-3: The histogram wise image enhancement is performed and the pixels with less quality are analyzed and those pixels contrast is enhanced. The pixels with less contrast will be identified using the similarity difference that is performed as

$$LCPix[M]=\sum_{i=1}^{M}\frac{\min\left(EHE(i,i+1)\right)}{M}+\mu(i,i+1)+\max\left(diff\left(EHE(i,i+1)\right)\right)$$

Here μ is the model considered for considering pixels with less contrast that has maximum difference from normal pixel range.

Step-4: Edge Detection identifies the edges of objects in a image. Edge detection process finds regions in images where there are abrupt changes in brightness, or discontinuities. The image's edges or boundaries are those spots where the brightness changes dramatically. The images edge detection is performed as

$$IED[M]=\prod_{i=1}^{M}\frac{maxrange\left(getPix(i)\right)-minrange\left(getPix(i)\right)}{M}+\lim_{i\to M}\left(simm\left(getPix(i+X,i+y)\right)+\frac{LCPix(i)}{M}\right)+getPix\left(diff\left(EHE(i+X,i+Y)\right)\right)$$

Where maxrange() is the pixels that are in maximum range than the specified threshold value, minrange() is the pixels set that are in minimum range than the specified threshold value. Diff() model calculates the changes in the pixel similarity levels that represents the shape.

Step-5: For image recognition systems, segmentation is a crucial step in the process since it allows us to isolate the objects of interest for tasks like description and identification. Image segmentation is a method for simplifying image analysis by dividing a digital image into smaller, more manageable pieces, or "Image Objects," made up of individual pixels. The proposed model segments the images based on the edge detected avoiding the noisy area for extracting only the relevant features. The segmentation is performed as

$$Iseg[M]=\prod_{i=1}^{M}\frac{\sqrt{\sum\max\left(IED(i,i+1)\right)}}{M-i}+\sqrt{\frac{\min\left(IED(i+X,i+Y)\right)+\max\left(simm(i,i+1)\right)}{M-i}}$$

M is the total number of images considered, simm() is used to identify the similarity among the pixels in adjacent regions.

Step-6: Feature extraction is a method for processing data that involves converting raw data into numerical features while keeping the original data set intact. Feature extraction involves splitting and merging a large dataset into smaller, more manageable subsets. This will make processing it easy when the time comes. Having a huge number of variables is the most essential attribute of these enormous data sets. It will need a lot of processing power to handle these variables. Feature extraction is a useful tool for decreasing the amount of data needed to extract useful information from large datasets by selecting and combining variables into features. The feature extraction is performed as

$$EFset[M]=\prod_{i=1}^{M}\frac{\sum_{j=1}Iseg(j)+\max\left(diff\left(Iseg(j,j+1)\right)\right)}{M}+maxrange(j,i)-minrange(j,i)+\frac{\max\left(simm(i,i+1)\right)}{\min\left(\text{diff(j,i)}\right)}$$

}

4. RESULTS

Melanoma is the most common type of skin cancer, and it is also the most dangerous and aggressive because it spreads so easily. Malignant melanoma develops when pigment-producing skin cells, called melanocytes, proliferate abnormally. Anywhere on the surface of the skin, known as the epidermis, might serve as a starting point for a path that eventually spreads to other areas of the body. Its incidence rate has been rising consistently to 5-7% each year and it has the highest mortality rate of all skin cancers. A five-year survival rate of up to 98% is possible with an early diagnosis, so it's obviously crucial. Diagnostic computer-aided technology analysis of medical images has received a lot of focus from researchers. For tasks like Region of Interest (ROI) segmentation and classification which, in this instance, involves identifying cancerous regions, these are tailor-made and fine-tuned. As the disease is most likely to have a delayed clinical start in its early stages, it is extremely important to detect and delineate lesion borders early on in order to effectively treat cancer. Every year, cancer affects around 18.5 million people, and almost 11.3 million of those people die because their treatment was delayed. Consequently, cancer has surpassed all other causes of death on a worldwide basis. The epidermis is the outermost layer of skin where skin cancer typically begins to grow, and it can affect both children and adults. Several computer-assisted methods have been proposed for the goal of detecting cancer borders from dermoscopy images.

Melanoma identification is complicated since benign and malignant skin lesions look quite similar. Melanoma diagnosis can be tough even for highly skilled medical practitioners for this reason. Visually identifying the sorts of lesions is a laborious and time-consuming procedure. Therefore, dermoscopy is one of the imaging procedures that have been utilized. Dermoscopy is a non-invasive imaging technique that can be utilized to observe the skin's surface by means of light-magnifying equipment and immersion fluid. One of the most popular imaging modalities in dermatology, it has reportedly increased the accuracy of cancer diagnoses by half, according to the observer's data. Nevertheless, melanoma detection in dermoscopy images manually may be inaccurate, subjective, or difficult to reproduce because it depends on the dermatologist's individual experience. Melanoma can be accurately diagnosed by a less experienced physician utilizing dermoscopy images 75% to 84% of the time. Because of all these difficulties, experts are looking for CAD model to aid in melanoma diagnosis. The next step for CAD systems in identifying a lesion as melanoma is to preprocess, segment, extract features, and classify the lesion. Lesion segmentation is a crucial part of CAD systems for accurate melanoma identification. Skin lesion size, color, texture, and position can vary greatly in dermoscopy images, making this segmentation stage quite tough. Due to the low contrast, it is impossible to distinguish the surrounding tissues.

Digital images can be more useful for viewing and further investigation with the help of image enhancement. Images can be enhanced using the histogram equalization procedure. Histogram equalization, which entails altering picture intensities, is one approach of enhancing image contrast. This method usually increases the overall contrast of many images when the relevant data is shown by close contrast values. The result of this adjustment is a histogram with more evenly distributed intensities. This allows areas with lower levels of local contrast to gain additional contrast. This is accomplished through enhanced histogram equalization, which makes the most frequent intensity values look less apparent. Enhanced Histogram equalization often produces fake effects in images. Enhanced Histogram equalization, when used on images with limited color depth, could occasionally provide undesirable results, including discernible image gradients.

By applying a structural element to an input image, morphological procedures generate an identically sized output image. Each pixel's value in the final image is determined by morphological operations, which compare each pixel in the input image to its neighbors. When it comes to image segmentation, morphological processes are frequently employed for the purpose of feature and object extraction, as well as image cleaning and smoothing. To thin out an image or eliminate fine features, one can use erosion; to enlarge or contract certain areas, one can use dilation. With the use of superior lesion segmentation from dermoscopy skin images, CAD methods can improve the accuracy of skin cancer diagnoses. Artifacts like irregularly shaped margins that share color with the lesions and/or hairs that lack contrast with the backdrop cause the present methods of skin lesion segmentation for dermoscopic images to generate substandard results. The proposed method will eliminate edges

from the supplied dermoscopy images. Aside from that, it will start looking for hairs and removing them if it finds any. After that, it removes the lesion features and applies image enhancing technique to make the final image better. Dermoscopy images containing hairs with low background contrast and/or differently sized corner borders colored like the lesion can benefit from the skin lesion segmentation method proposed in this study. This research presents an Enhanced Histogram Integrated Morphological Image Quality Enhancement Model using Dermoscopy Images with Edge based Segmentation (EHIMIQE-DIES). The proposed model is compared with the traditional Active Contours Based Segmentation and Lesion Periphery Analysis for Characterization of Skin Lesions in Dermoscopy Images (ACbSLPA) and autoSMIM: Automatic Superpixel-Based Masked Image Modelling for Skin Lesion Segmentation (autoSMIM). The results represent that the proposed model performance in image quality enhancement and segmentation is high than the traditional models.

By applying a structural element to an input image, morphological procedures generate an identically sized output image. Each pixel's value in the final image is determined by morphological operations, which compare each pixel in the input image to its neighbors. The Morphology Operations Time Levels of the proposed and existing models are represented in Table 1 and Figure 4.

Table 1: Morphology Operations Time Levels

Images Considered	Models Considered		
	EHIMIQE-DIES Model	ACbSLPA Model	autoSMIM Model
200	17.0	20.1	22.5
400	17.3	20.3	22.7
600	17.5	20.4	22.8
800	17.7	20.6	23.1
1000	17.9	20.8	23.3
1200	18	21	23.5

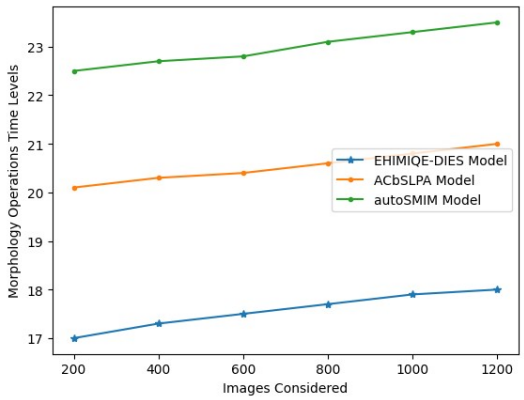

Fig 4: Morphology Operations Time Levels

Histogram equalization is a method for improving images. One way to improve contrast in images is by using histogram equalization, which involves modifying image intensities. When the image's useful data is represented by close contrast values, this strategy typically boosts the global contrast of several images. Using image processing techniques including color space conversion, image inversion, dehazing, saturation enhancement, an enhanced histogram equalization based local contrast preserving method is designed in this research for enhancing the image quality. The Enhanced Histogram based Image Enhancement Accuracy Levels are shown in Table 2 and Figure 5.

Table 2: Enhanced Histogram based Image Enhancement Accuracy Levels

Images Considered	Models Considered		
	EHIMIQE-DIES Model	ACbSLPA Model	autoSMIM Model
200	97.5	93.4	93.9
400	97.7	93.6	94.0
600	97.9	93.8	94.1
800	98.0	94.0	94.3
1000	98.2	94.1	94.5
1200	98.4	94.3	94.8

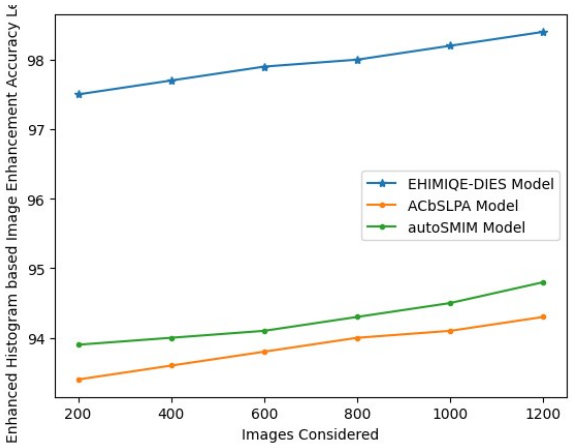

Fig 5: Enhanced Histogram based Image Enhancement Accuracy Levels

Images can be enhanced for display or additional analysis through a process known as image augmentation. Visual perception and comprehension of visuals are made easier with the application of enhancements. The ability to alter the values of individual digital pixels is a major benefit of digital images. The Image Enhancement Accuracy Levels are indicated in Table 3 and Figure 6.

Table 3: Image Enhancement Accuracy Levels

Images Considered	Models Considered		
	EHIMIQE-DIES Model	ACbSLPA Model	autoSMIM Model
200	97.9	94.1	93.6
400	98.1	94.3	93.8
600	98.2	94.6	94.0
800	98.4	94.8	94.3
1000	98.6	94.9	94.5
1200	98.8	95	94.7

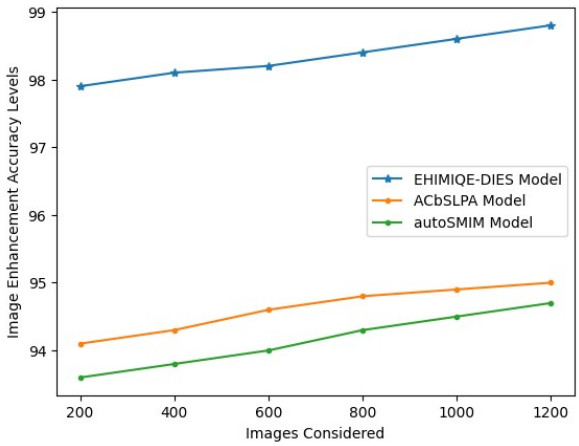

Fig 6: Image Enhancement Accuracy Levels

The purpose of edge detection, image processing technique, is to locate regions in a digital image that have abrupt changes in brightness, or discontinuities. The edges of an image are those spots where the brightness of the image changes dramatically. One way edge detection works is by looking for changes in brightness that don't blend in. Its primary applications are data extraction and image segmentation. The Edge Detection Time Levels are represented in Table 4 and Figure 7.

Table 4: Edge Detection Time Levels

Images Considered	Models Considered		
	EHIMIQE-DIES Model	ACbSLPA Model	autoSMIM Model
200	13.1	16.7	17.3
400	13.3	16.9	17.5
600	13.5	17.1	17.8
800	13.6	17.3	18.0
1000	13.8	17.5	18.2
1200	14	17.6	18.4

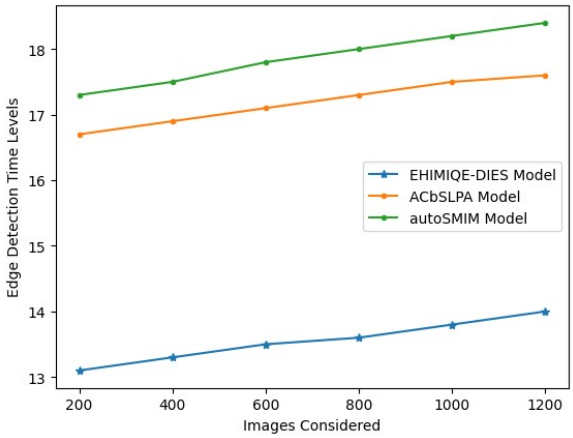

Fig 7: Edge Detection Time Levels

Digital image processing and analysis frequently employ image segmentation as a method to divide an image into multiple regions, typically according to pixel properties. For example, image segmentation could involve dividing the foreground from the background or grouping pixels into regions with shared colors or shapes. Segmentation is a crucial step in image recognition systems as it extracts the objects of interest for subsequent processing, like description or recognition. The Segmentation Accuracy Levels of the proposed and existing models are shown in Table 5 and Figure 8.

Table 5: Segmentation Accuracy Levels

Images Considered	Models Considered		
	EHIMIQE-DIES Model	ACbSLPA Model	autoSMIM Model
200	97.6	93.2	92.7
400	97.9	93.5	92.9
600	98.1	93.7	93.0
800	98.3	93.9	93.2
1000	98.5	94.0	93.5
1200	98.7	94.1	93.8

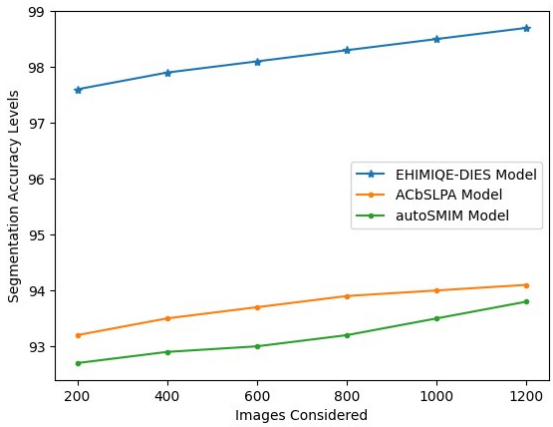

Fig 8: Segmentation Accuracy Levels

When working with high-dimensional data, feature selection is a crucial method for lowering the dimensionality. In feature extraction, a set of F features is chosen from a dataset of M features, where F is less than M. As a result, the cost of certain evaluation functions or measures can be improved over all potential feature subsets. In order to decrease training time and minimize complexity of the created classification models, the non-dominant features are removed throughout the feature extraction process. The Feature Extraction Accuracy Levels are indicated in Table 6 and Figure 9.

Table 6: Feature Extraction Accuracy Levels

Images Considered	Models Considered		
	EHIMIQE-DIES Model	ACbSLPA Model	autoSMIM Model
200	97.8	94.3	93.8
400	98.0	94.6	94.0
600	98.1	94.8	94.1
800	98.2	95.0	94.3
1000	98.4	95.1	94.5
1200	98.6	95.3	94.7

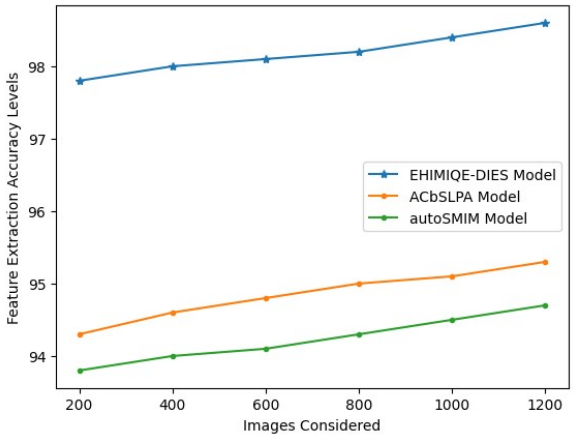

Fig 9: Feature Extraction Accuracy Levels

5. CONCLUSION

Dermoscopy images with corner borders of different sizes or borders of a color that is similar to the lesion frequently provide misleading lesion segmentation findings when using the current skin lesion segmentation methods. The proposed skin lesion segmentation technique addresses this issue by utilizing a novel border removal method. This method can remove borders of varied sizes and colors that are comparable to the lesion, improving the lesion segmentation results. An algorithm for improving contrast and detail was introduced in this study. The image is enhanced at various scales using this combination of processes, which are strategically applied to bring out the image's useful qualities like details and edges. Dermoscopy images of skin lesions can now be automatically segmented using this technology. Clinicians can better pinpoint the precise site of skin lesions using the suggested automated segmentation technology, which aids in future diagnostic procedures. Prior to skin lesion segmentation, the input image undergoes pre-processing to eliminate artifacts such as bubbles and hair and to fix illumination variation. All skin lesions are removed after pre-processing. In order to improve the segmented image, the segmented image is processed afterwards via edge recognition, background subtraction and using several morphological operators. Obtaining the precise area of the lesion blob in this way can aid in subsequent processing. This research presents an Enhanced Histogram Integrated Morphological Image Quality Enhancement Model using Dermoscopy Images with Edge based Segmentation. The proposed model achieved 98.7% accuracy in segmentation and 98.6% accuracy in feature extraction. In future, hybrid models can be applied on the image enhancement and segmentation model for accurate extraction of the lesion regions.

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