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Deep Learning-Based Approach for Skin Lesion Classification and Melanoma Detection

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Abstract

Skin cancer is one of the most frequent malignancies in the world, and its incidence is rising as people age. In general, it is best to diagnose skin cancer as soon as possible. Melanoma is a dangerous form of skin cancer that has been more prevalent worldwide over the past few decades. As a result of medical professionals' efforts to find a cure, automatically identifying skin lesions using dermoscopic pictures has remained a difficult and complex task. Indistinct lesion borders, poor color contrast, location dependence, form fluctuations, and complicated lesion structures are some of the variables that contribute to this type of difficulties in lesion diagnosis. Medical personnel and researchers can save many lives if the growing public health burden issues are identified early and treated appropriately to stop them from spreading to other body organs. There is a possibility that the person may have melanoma if there is an unusual change in the skin's appearance. Dermatology expertise must be integrated with computer vision methods for effective melanoma detection in order to achieve improved results. Therefore, it's critical to create a variety of detection methods to help medical professionals identify melanoma in its early stages. The proposed model presents an intelligent and integrated framework for automated melanoma detection that combines adaptive pre-processing, information-theoretic segmentation, discriminative feature extraction, and optimized deep classification. An Information-Gain–Driven Morphological–ABCD Feature Fusion (IGM-ABCD-FF) framework is proposed to adaptively refine clinically significant lesion features prior to deep residual classification.

Keywords: location dependent, Skin, melanoma, dermoscopy

1. Introduction

One extremely dangerous and aggressive type of cancer is skin cancer. Skin cancer can only be cured if it is discovered in its early stages. The skin is essential to the human body and covers all of the body's anatomical elements, including the muscles and bones. Hundreds of thousands of individuals worldwide suffer from melanoma, a severe and potentially fatal skin disease. In order to treat melanoma quickly, many creative challenges or methods are needed in the medical field. Researchers must examine earlier research-based literature surveys conducted at various times and locations in order to discover a better treatment for the deadly skin illness melanoma. An improved understanding of the research environment in the relevant field can be obtained by a study of related publications. It assists the researcher in starting his work in the correct direction and applying objective ways to any issues with medical image processing in general and melanoma treatment using novel techniques in particular [1]. In dermatology, medical patterns including colors, veils, pigmented nets, globs, and ramifications can be better seen with a magnifying lens and light. The morphological structures that are otherwise hidden are visible to those who are blind or visually handicapped. [2]. The predictive value of non-professional dermoscopic pictures for melanoma is between 75% and 80%; however, the interpretation is quite subjective and takes time, depending on the dermatologist's experience. Overcoming these challenges has been made simpler by computer-aided diagnosis (CAD) techniques. Artificial Intelligence (AI) based on Deep Learning (DL) has greatly advanced CAD of cancers.

Fig. 1. Dermatoscopy and Dermatoscopic image

Because dermatologists and labs are few in rural regions, automating skin cancer screening and early detection could be facilitated by employing DL techniques to identify skin lesions. The real use of DL-based dermoscopic images has produced incredible achievements during these exciting scientific developments. However, a number of challenges, including insufficient training data and unbalanced datasets, particularly for uncommon and similar lesion types, impede further advancements in diagnosis accuracy [3]. In this study, An Information-Gain–Driven Morphological–ABCD Feature Fusion (IGM-ABCD-FF) framework is proposed to adaptively refine clinically significant lesion features prior to deep residual classification. The main contributions of the work can therefore be summed up as follows:

- To develop an adaptive morphological pre-processing framework that effectively suppresses noise and enhances critical lesion structures in dermoscopy images.
- To design an Information-Gain–Guided Multi-Layer Morphological Segmentation approach for accurate isolation of skin lesion regions by adaptively selecting threshold levels and refining lesion boundaries.
- To extract clinically meaningful ABCD-rule features in combination with statistical and texture descriptors to comprehensively represent melanoma characteristics.
- To implement an Information Gain Ratio–based feature evaluation and Sequential Forward Selection mechanism to identify the most discriminative and non-redundant feature subsets.
- To construct a deep residual neural network–based classification model for robust categorization of skin lesions into benign, malignant, and normal classes.
- To achieve reliable classification performance across varying lesion sizes, textures, and illumination conditions, ensuring robustness and generalizability of the proposed framework.

2. Review of literature

In addition to using the healthier skin surface from dermoscopy pictures for more accurate disease detection, Santhi et al. (2019) suggest an automated lesion analyzer to deal with the affected area of skin lesion. Neural networks (NNs) are thought to be the greatest data-driven models in all domains, offering increased accuracy that has been tested up to this point. It requires a great deal of processing power to train the model using input dermoscopy images, and it also makes predictions using embedded systems and handheld devices [5]. The suggested model can be further improved by adding dropout techniques to regularize the model and learning rates. This will also result in global minima with plateaus. An automatic system to enhance classification performance for the effective diagnosis of melanoma is proposed by Seeja et al. (2019). Using a deep learning approach based on the U-Net algorithm, the lesion region is segmented from the dermoscopic pictures. Convolutional neural networks are then used to extract distinctive properties. Melanoma is classified using the VGG16 Net method, which indicates whether the lesion is benign or malignant. Two categories, such as the classification with or without segmented images, are used to determine the classification results. The ISIC 2016 dataset is used for the evaluation, and it is found that deep learning-based classification using segmented images yields better results for enhancing diagnosis performance [6]. By including probabilistic graphical models into this network, the work can be expanded.

Muhammad Nasir et al. (2018) offer a technique that helps the CAD system identify melanoma early on, which can lower death rates. Preprocessing, lesion segmentation, feature extraction, feature selection, and classification are some of the steps in the suggested method. DullRazor is used for pre-processing and hair removal, which also improves the lesion's contrast. Color, texture, and HOG features are retrieved, and the distribution of local intensity gradients can be used to categorize the lesion's shape and appearance [7]. With improved accuracy and efficiency, the newly proposed diagnostic techniques are quite advantageous. The 200 photos in the publicly accessible dataset PH2, which yields noticeably better results when compared to the current techniques, are used for validation. Therefore, it is determined that SVM support yields better results on entropy-based features, which may be effectively applied using the Boltzman Entropy technique.

The crucial stage of an automated computer-aided diagnosis method for identifying the presence of melanoma using lesion segmentation is presented by Euijoon Ahn et al. (2017). Some of the technical issues with the traditional segmentation methods include poor skin lesion segmentation performance due to imprecise lesion borders, low contrast between the lesion and surrounding skin, and lesions touching the edges of the image [8]. The pattern recognition method is proposed by Tammineni Sreelatha et al. (2019) for melanoma early diagnosis and mortality rate reduction. The segmentation method that is crucial for the early detection of melanoma in dermoscopy pictures is the Gradient and Feature Adaptive Contour (GFAC). Pre-processing is used as the first stage prior to segmentation in order to lower the amount of noise in the image. In order to effectively extract the features that are found throughout the feature extraction process, the approach makes use of several Gaussian distributed patterns. After evaluating the PH2 dataset and validating the efficiency using other cutting-edge methods, it is concluded that the suggested method's disc similarity coefficient yields superior results [9]. Marwan Ali Albahar et al. (2019) describe a deep learning-based Convolution Neural Network that can use dermoscopy pictures to predict even the smallest skin changes. Medical screening using dermoscopic analysis, biopsy, and histological evaluation is typically the first step in the diagnosis process for skin cancer. The suggested framework, known as novel regularized, uses a binary classifier to efficiently classify the lesions. Finding the area under the curve for nevus and comparing it with the lesion images for an effective diagnosis validates the performance.

3. Methodology

This technique's main goal is to use dermoscopy pictures to predict the presence of melanoma from skin lesions. The pre-processed stage is intended to make procedures easier, which may detect extraneous artifacts during the process. It is mapped using the image segmentation approach to identify the lesion. The localized lesions are used for classification after being measured using characteristics.

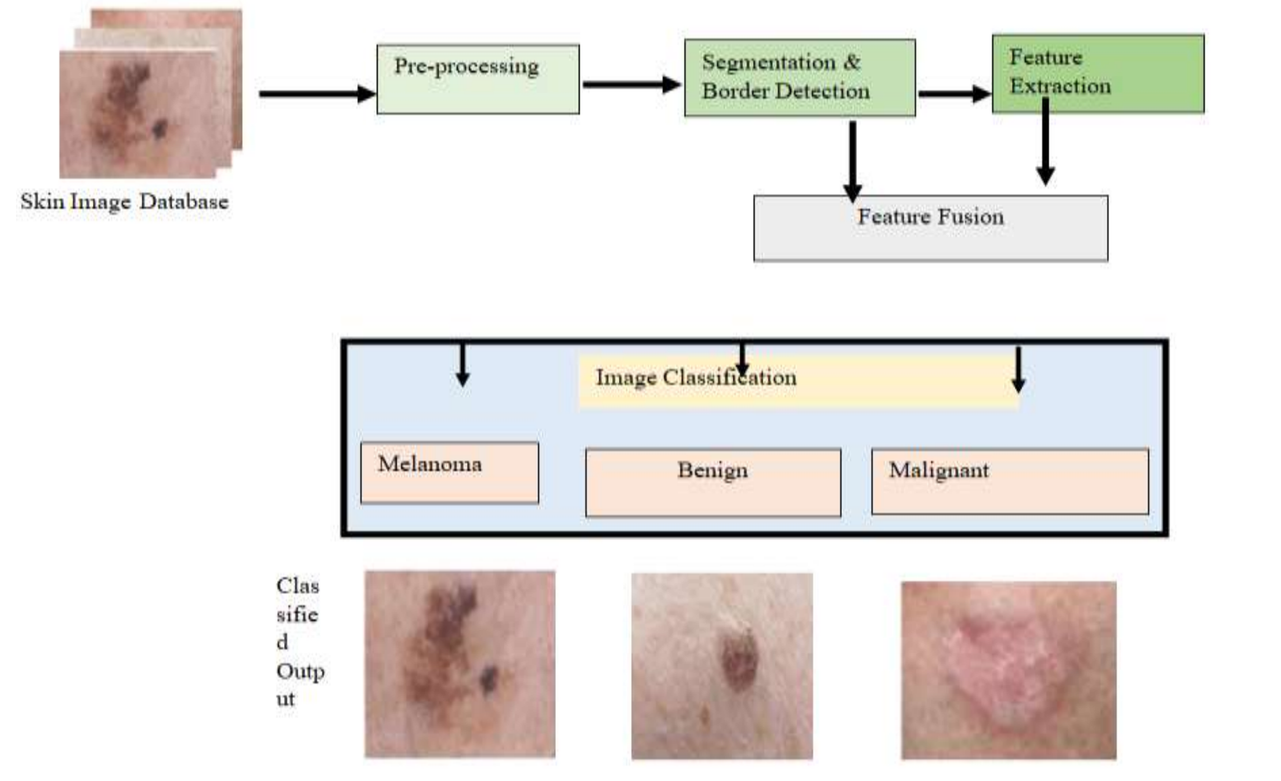


Fig. 2. Overall Images

Melanoma images must be distinguished from dermoscopy images using extremely quick image preprocessing, segmentation, and classification of the derived characteristics. As a result, a thorough analysis is necessary to choose the best option and establishes the standard for the development and validation of analytical categorization. This concept is used in the current study, and a revised paradigm for melanoma diagnosis is provided. Numerous studies have focused on the creation of a CAD treatment for skin cancer. CAD systems have used traditional machine learning techniques to process images of skin lesions in accordance with the usual medical image analysis pipeline. Image preparation, feature extraction, fragmentation, and classification have all been done repeatedly in this process with varying degrees of success. While deep learning may automatically take use of the deep nonlinear correlations in the images, traditional image recognition algorithms require feature estimation and extraction [10].

Initially, the input dermoscopy images undergo Adaptive Morphological Processing to suppress noise and enhance lesion structures. An Information-Gain–Guided Multi-Layer Morphological Segmentation strategy is then employed to accurately isolate lesion regions by adaptively selecting threshold levels and refining boundaries using morphological operations and edge linking. From the segmented lesions, clinically significant ABCD-rule features along with statistical and texture descriptors are extracted and refined through Information Gain Ratio–based feature evaluation and Sequential Forward Selection to remove redundancy. Finally, the optimized feature set is fed into a deep residual neural network to effectively classify skin lesions into benign, malignant, and normal categories, achieving robust performance across varying lesion sizes, textures, and illumination conditions.

3.1. Dataset

Melanocytic and pigmented skin lesions can be examined non-invasively using dermoscopy, also known as epi luminescence microscopy (ELM). This process is carried out by applying a dermato scope—a portable, lighted microscope—to the skin's surface. A transparent plate, a non-polarized light source, a high-quality lens with a 10-fold magnification, and a liquid medium between the device and the skin make up this optical system. It is utilized for the histological and clinical correlation of lesions and permits the examination of skin lesions without being hindered by skin surface reflections.Dermatoscopy makes it possible to visualize submacroscopical structures, evaluate colors in vivo, and greatly increase the diagnostic accuracy of melanoma. It assesses characteristics like vascularization patterns and pigment distribution and aids in the development of regression structures that are not visible to the human eye.The Skin Image Database (SID) [10] is a publicly accessible dermatological image database created to facilitate research on automated skin lesion analysis and melanoma detection. The database consists of high-resolution dermoscopic images of different skin lesions, including benign nevi, melanoma, basal cell carcinoma, and other pigmented skin lesions. Each image is annotated by certified dermatologists, offering a trustworthy source of ground truth labels for learning algorithms. The database is typically employed for both binary classification (melanoma vs. non-melanoma) and multi-class lesion classification. The images are usually of varying sizes and are captured under standardized dermoscopic settings to ensure homogeneity in terms of color, texture, and lesion boundaries. The Skin Image Database is very important in the development of deep learning-based diagnostic tools, as it allows convolutional neural networks to learn features of asymmetry, border irregularity, color, and texture of malignant skin lesions. Because of its clinical significance and variability in skin lesion types, the database is commonly used for training, testing, and evaluating automated melanoma detection systems.

Fig. 3. A sample of skin lesions of melanoma from the used data

3.2. Preprocessing: Adaptive Morphological Processing

Image conversion, contour detection, wavelet transform, ABCD parameters, segmentation, and feature extraction are the six sub-components used in this data pre-process [11]. In this case, the suggested model employs distinct new and current techniques for image conversion, contour detection, wavelet transformation, frame ABCD rules, segmenting the input melanoma images, and extracting the required features from the input image.

$$I(ST1, ST2, \dots. STn) = \sum_{i=1}^{n} \left(\frac{ST_i}{st}\right) log_2 \left(\frac{ST_i}{st}\right) \qquad (1)$$

A feature Ft with their values $\{FS_1 , FS_2, ..., FS_V\}$ will split into different training image data set into the various ‗v ‘number of image subsets {ST1, ST2,...., STv} where ST_i is indicating the image subset that has the separate image data value fS_j for the feature Ft. Moreover, consider ST_j contain $ST_{i,j}$ sample image data ‘s of the class i.

$$\mathrm{E(Ft)} = \sum_{j=1}^{v} (ST_{1j} + \dots \dots\ ST_{nj}) / ST\ *\ I(ST_{1j} + \dots \dots\ ST_{nj}) \qquad (2)$$

The IG for the specific feature F is computed as in Equation

$$\mathrm{IG(Ft)} = \mathrm{I}(ST_1, ST_2, \dots\ \dots . ST_n) - E(Ft) \qquad (3)$$

The classification module, which performs the picture classification process, receives this data pre-processor [12]. Each output pixel's value during a morphological operation is ascertained by comparing it to its neighbors in the input image. There is some overlap between morphology and image segmentation.

$$SI(XV) = -\sum_{i=1}^{n} \frac{|TS_i|}{|TS|} log_2 \frac{|TS_i|}{|TS|} \qquad (4)$$

Morphology comprises methods that can be used either as a pre-processing method on the input data or as a post-processing method on the output of the image segmentation stage. A pixel in the newly processed image is assigned to each pixel in the original image that the structuring element is moved across [13]. The morphological operation that was performed determines the value of this new pixel.

$$IGR\ (DS, TS) = \frac{Gain\ (DS, TS)}{SI\ (DS, TS)} \qquad (5)$$

One kind of morphological image processing is dilation. OpenCV morphological image processing is used to alter an image's geometric structure. We learn about an object's size, shape, or structural characteristics through morphism. Despite being defined for binary pictures, both techniques can be used with grayscale images. These are frequently used to remove noise, identify any regions of the image with uneven or absent intensity, and separate different components from one another before merging them into a single image. Dilation adds pixels to an object's edges or enlarges the image's pixels.

3.3. Segmentation: Information-Gain–Guided Multi-Layer Morphological Segmentation (IG-MLMS)

The process of separating and subdividing an input image into its constituent areas and extracting these regions of interest, which are all the image objects, is known as image segmentation. Effective picture segmentation can be achieved using a variety of techniques, particularly when segmenting grayscale images. This segmentation's primary goal is to characterize the following features. In this case, the data set is referred to as p-dimensional data $X = \{x_1, x_2, \dots . , x_n\} C\ R^p$Additionally, P must be uniformly predicated in order to obtain a partition of the provided picture collection into multiple disjoint nonempty groups $\{C_1, C_2, \dots . , C_n\}$which are subject to the given below conditions:

$$U_{i=1}^{K} C_i = X \qquad (6)$$

$$C_i \cap C_j = \varphi, \quad i \neq j \qquad (7)$$

$$P\ C_i = TRUE, \quad i = 1,2, \dots . . k \qquad (8)$$

$$P\ C_i \cap C_j = FLASE, \quad i \neq j \qquad (9)$$

In this case, all data must be allocated to a single group under the first criterion. In the second condition, the specific group is given a data value [19]. The third and fourth conditions require that all of the data in a single group satisfy the evenness predicate while the data values from different groups fail the evenness criteria.

$$v = Max\ (R, G, B) \qquad (10)$$

$$S = \frac{V - Min\ (R, G.B)}{V}, V \neq 0 \qquad (11)$$

$$\mathrm{S} = 0, \mathrm{V} = 0 \qquad (12)$$

If S = 0, then H =0. If R = V, then, the hue value could be calculated as follows in order to find the intensity of the affected skin lesion, If G = V, then the combinations of R, G, B values are designated to calculate the —H value as follows

$$H = \begin{cases} \dfrac{(G - B)}{V - Min\,(R, G.B)}, & G \geq B \\ \dfrac{(G - B)}{V - Min\,(R, G.B)}, & G < B \end{cases} \quad (13)$$

However, there may be at least two objects in very complicated medical imaging. By choosing depending on the threshold, which is at least two, the medical image in this case is split into at least three parts. One term for this threshold procedure is a multilayer threshold. In the past, numerous researchers used this thresholding method to develop different approaches in this area. The objective of the Information-Gain–Guided Multi-Layer Morphological Segmentation (IG-MLMS) procedure is to identify the edges of each region in the input image by determining the proper spots where the intensity values vary dynamically. All of these discontinuities are often found by applying a mask to the medical image.

By using the varied values for the coefficients in the mask, one might search for the different types of edges in an image [14]. Additionally, some edge linking operations must be completed because the edges created by applying various masks to the medical image may not have full limits. Masks are used to identify edges with lengthy stories, and numerous methods have been created to do this goal.

3.4. Feature Extraction: ABCD Rule-based Feature Extraction

The segmented pre-processed pictures might be subjected to specialized computations during the feature extraction process. The primary goal of this feature extraction is to create a new feature vector—a real number—from medical photos that explains the essential characteristics of the provided medical images. As a result, every single image must also be represented by a point in a feature space, which is a set of n dimensional spaces.

$$J(U, M) = \sum_{i=1}^{p} \sum_{j=1}^{c} (U_{i,j})^m d_{i,j} \quad (14)$$

Building a new feature space with easily separable intrinsic image classes (benign/malignant) is the goal of the feature extraction method [14]. The majority of feature extraction techniques used to extract features from skin cancer photos suggest new features that are modelled using the ABCD rule by medical professionals in a clinical setting.

$$Lv\,(k\,, l) = \sigma^2 \frac{1}{n^2 - 1} \sum_{k=1}^{n} \sum_{l=1}^{n} ((k, l) - \bar{f}\,)^2\,, for \begin{matrix} k = 1,2, \ldots.M \\ l = 1,2, \ldots., N \end{matrix} \quad (15)$$

where (k, l) denotes the local image's coordinator, the sub-image f, and the skin cancer image's grey level, which also functions as the neighbors' mean value.

$$u_{i,j}^{(t+1)}(t_1, t_2) = \frac{1}{\left(\sum_{t=1}^{p} (\frac{d_{i,j}}{d_{i,j}}) 1/(1-m)\right)} (t_1, t_2) \quad (16)$$

$$||M^{(t+1)} - M^t||(t_1, t_2) < \varepsilon \quad (17)$$

The equation is applied throughout the medical image processing procedure to slide the window location "from left part of the skin cancer image and to the right part of the skin cancer image".

3.5. Feature fusion: Information Gain Ratio-based Feature Fusion

Information Gain Ratio-based Feature Fusion architecture was created, for prediction performance.

$H = f(WX + b)(18)$

Subsequently, the visual appearance of the input feature representation from the low-dimensional representation H.

$\hat{X} = g(W'H + b')(19)$

In this context, X̂ represents the acquired feature representation, while W', b', and g(·) refer to the decoder's weight, bias, and decoding function, accordingly. In order to reduce the reconstruction error, we establish a cost function through the process of

$$E = MSE + \lambda \times \Omega_{sparsity} + \beta \times \Omega_{weights} \quad (20)$$

The parameters λ and β represent the sparsity regularization and the coefficients for L2 regularization, correspondingly. By averaging the marginal contributions across all possible combinations.

$$\emptyset_0 = \frac{1}{N}\sum_{j=1}^{N} f(x^{(i)}) \qquad (21)$$

$$\emptyset_i(x_i^{(j)}) = \emptyset(x_i^{(j)}) - \frac{1}{N}\sum_{K=1}^{N} \emptyset(x_i^{(K)}) \qquad (22)$$

$$f(x^{(i)} = \emptyset_0 + \sum_{i=1}^{K} \emptyset_i\,(x_i^{(j)}) \quad (23)$$

where N is the patient count. It has been demonstrated that the SHAP value is reliable and may be used to explain the variety of ML techniques, such as Generalized Linear Models (GLM). The relationship between an Information Gain Ratio-based Feature Fusionis as follows:

$$\emptyset_{\boldsymbol{GLM}}(x_i^{(j)}) = a_i x_i^{(j)} - E(a_i x_i) = a_i x_i^{(j)} a_i E(x_i) \quad (24)$$

The consistently the feature influences the model's predictions.

$$X_i' = \frac{X_i - X_{min}}{X_{max} - X_{min}}, \qquad F = W_1 X_1' + W_2 X_2' + \ldots + W_n X_n' (25)$$

Data normalization balanced feature inputs for machine learning or deep learning models, especially in healthcare analytics and diagnostic pipelines.

$$Z_i = \frac{X_i - \mu_i}{\sigma_i}, \qquad \mathrm{F} = [Z_1||Z_2||\ldots||Z_n] \qquad (26)$$

This fusion strategy preserves the complete information from each data type while enabling deep learning models to learn cross-modal relationships, making it highly effective for multimodal diagnosis, prognosis prediction, and decision-support systems.

3.6. Optimal Feature Subset

pre-trained on a sizable collection of generic picture data, and then extra layers were added for the particular goal of skin lesion classification. This method enables identifying the distinctive features of various lesion kinds by utilizing the pre-trained network's general pattern recognition knowledge. If the token delivered to the server corresponds to what is specified in the request, the server will display a response.

$$I_a^{grey}(r\,,c) = \frac{R(C[r\,,c]) + G(C[r\,,c] + B(C[r\,,c])}{3} \qquad (27)$$

Where $C[r\,,c]$ represents the colour skin lesion images and presence of specific colours in lesions are described in variables R, G and B, (r, c) that denote the achieved grey scale images, and the parameter $I_a^{grey}(r\,,c)$ describes the row and column of the indexes individually.

$$B_a = \sum_{c=0}^{a} Hist\ (c) = W^2 - \sum_{c=a+1}^{A-1} Hist\ (c) \qquad (28)$$

In terms of decision-making in the suggested prediction model, this subcomponent is in charge of extracting the essential elements that can contribute more to the picture classification process [15]. In this case, a set of measured data is used to build the derived features, which must be helpful, instructive, and non-redundant. In this data pre-processor, it typically reduces dimensionality.

3.7. Classification: Deep Residual Network Classification

Based on the segmentation results, a deep residual network has been built to classify skin lesions. The neural network, which is trained independently and end-to-end using the residual network methodology, is used to produce the anticipated results. The carefully chosen features are utilized to identify and categorize benign, malignant, and normal lesions. This can be done across a variety of classifiers that have been investigated. The cutaneous lesions typically vary greatly in size. Both the training and testing performance involved in the skin lesion categorization are significantly impacted by the differences in lesion size of dermoscopy pictures [16]. By segmenting the skin lesions from dermoscopy images, resizing the lesions to a fixed size, and performing classification on the post-processed dermoscopy images, these problems can be resolved. The Neural Network's (NN) weight update minimizes the discrepancy between the real and classifier output.

The following equations are used to calculate classification,

$$Coh_g = \frac{\sum_{h=1}^{M} K_h}{M} - K \qquad (29)$$

where the term K represents the position of the current individual, K_h position of h-th neighboring individual and the variable M is the number of neighboring individuals.

$$Aln_g = \frac{\sum_{h=1}^{M} Vel_n}{M} \qquad (30)$$

Where Vel_n shows the velocity of h-th neighboring individual. The separation of g-th dragon fly,Sep_g from its neighbors is computed using the Equation (30).

$$Sep_g = -\sum_{h=1}^{M}(K - K_h) \qquad (31)$$

$$ATT_g = F - K \qquad (32)$$

where the location of the food source is represented by the attribute F. The Equation can be used to validate the last parameter, distraction (16).

$$K_{it+1} = K_{it} + \Delta K_{it+1} \qquad (33)$$

The dragon fly improves the randomization and stochastic aspects of exploration by moving around the search space with the help of a random levy walk when it finds no nearby solution. The following formulae are currently used to update the dragonflies' positions,

$$K_{it+1} = K_{it} + Levy(dpv) \times K_{it} \qquad (34)$$

Additionally, it is recommended to do a feature selection test in order to determine the relative relevance of each feature and select the best subsets of features [17]. Although there are several approaches to finish this task, the SFS approach is recommended. SFS has used a classifier with an embedded-oriented feature selection technique to evaluate the performance of various feature pairs. According to the SFS, the features selected for this study employ a ten-fold cross-validation structure to assess each feature's performance.

$$C(x, y) = \frac{1}{2\pi\sigma^2} exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \qquad (35)$$

Since it has the highest significance (distinction strength) of all the features, the first component of the ideal feature subsets has been found to reflect the feature and the relevant metrics. The best collection of features from two different individuals is obtained by combining the first picked feature with the other selected features; collections of features from both individuals are created and assessed in the same way. The three-membered categories, which are produced when the two-membered grouping combines with other attributes, are also used for the assessment. This approach is repeated until all currently available functions are included in the final list of features.

$$EC = {ED}/{\sqrt{A_L}} \tag{36}$$

Cutaneous melanoma is the type of melanoma that first manifests in the skin and seems to be more prevalent. There are three typical types of this. Initially, up to 70% of cases are of a very common type of melanoma called "superficial propagating melanoma," which usually arises around an existing mole. Malignant melanomas associated with lentigo syndrome are common in older adults. Skin layers that are typically exposed to sunlight are where this normally starts. A lesion's texture provides crucial information in classification [18]. Color and shape characteristics alone may not be sufficient to differentiate between benign and malignant tumors because they can have similar form or color characteristics. Nonetheless, it was discovered that combining these characteristics with textural characteristics greatly facilitated the identification of melanoma.

4. Result and discussion

The experimental results of these three-performance metrics such as sensitivity, specificity and the detection accuracy of the proposed model for detecting the melanoma. The following clearly shows that the majority cases of malignant melanoma that are diagnosed correctly with reasonable detection rate during only in two different cases in which the benign skin lesions were diagnosed wrongly as malignant melanoma. In addition, it must be highlighted which is established as an experimentally due to the fact that the extraction of local HOG attributes not only avail a good prospective for promoting the quantitative discrimination between the normal skin image and the melanoma affected skin image, but they turn out also for robust fully to the various kinds of melanoma skin cancer. Generally, this work conclude that the results demonstrate the supporting evidence which is the proposed framework that used to enhance the performance of the detection of melanoma skin cancer disease early without forgoing its real time assurances.

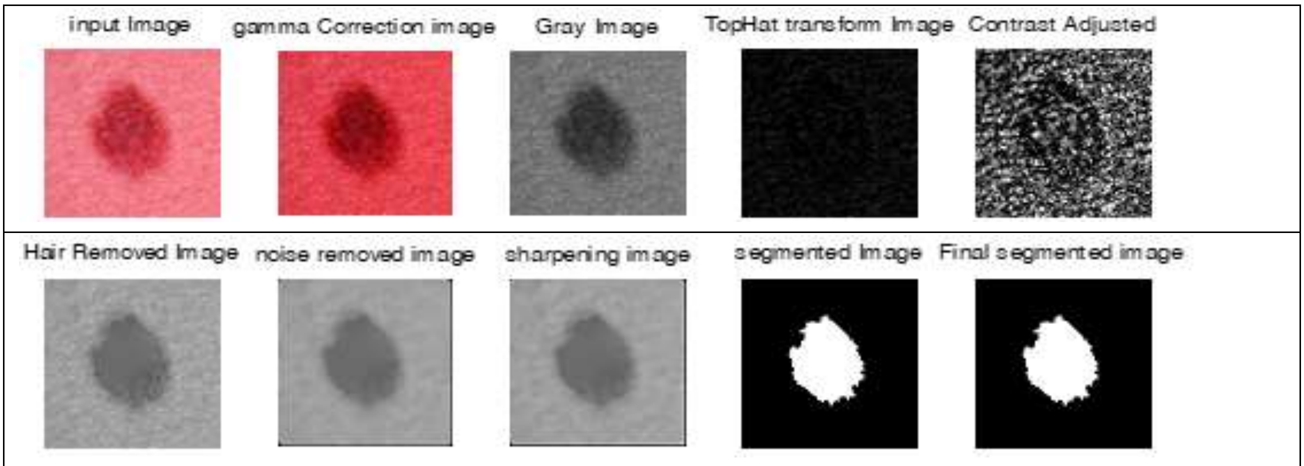


Fig. 4. segmentation results

After a number of tests, the model that was put into use on the server was chosen because it demonstrated the highest level of accuracy out of all the models that were trained and assessed. In particular, the model was trained to identify seven distinct kinds of skin lesions using a transfer learning-based approach (figure 4 and 5).

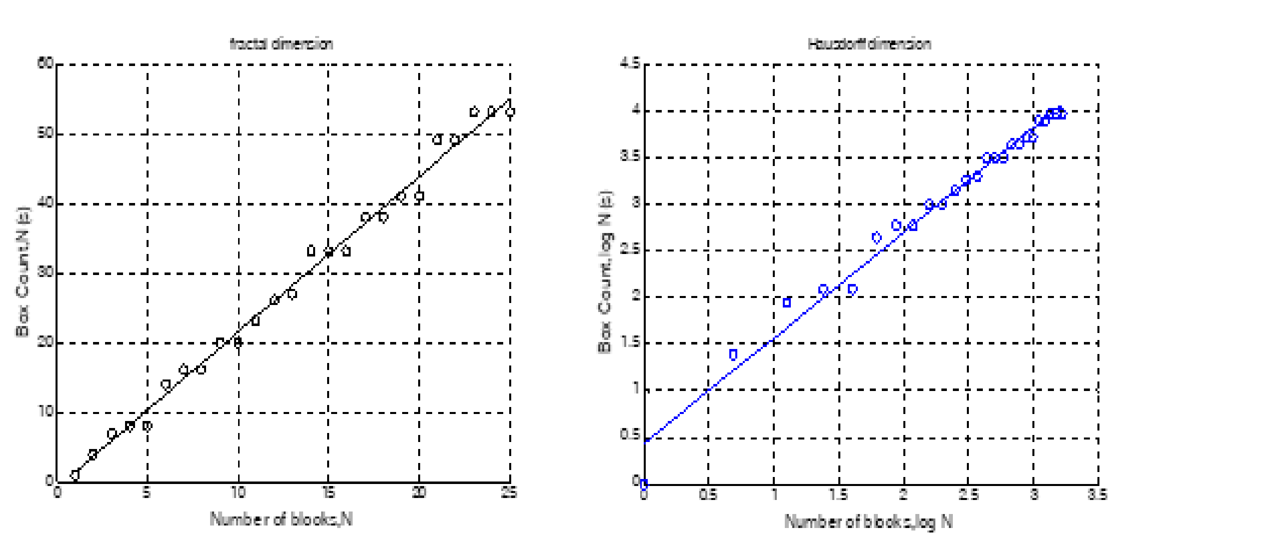
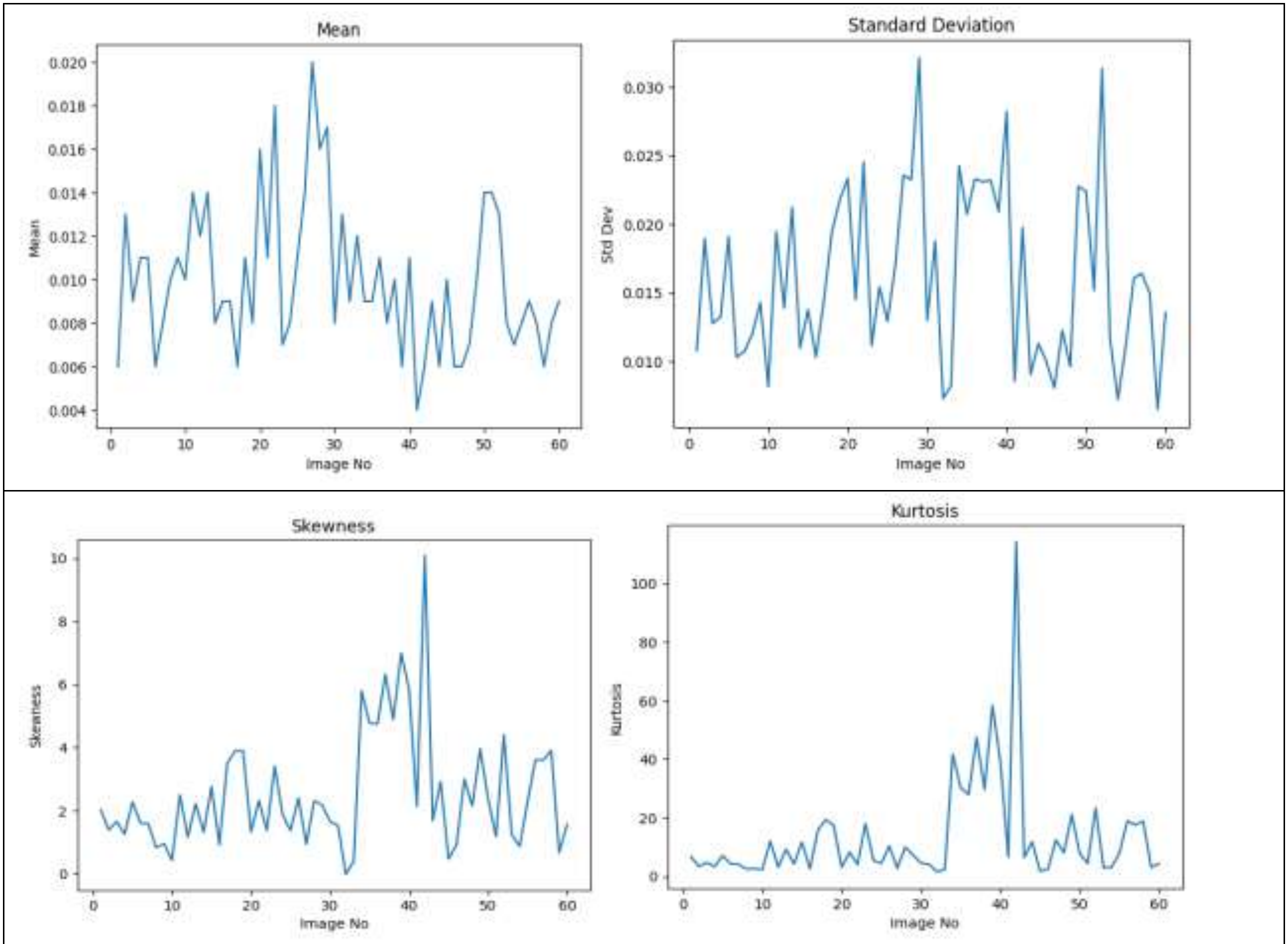


Fig. 5. Benign skin image-segmentation & fractal feature diagram

Every system in the body is greatly impacted by a small change in the skin's functioning, making it a major player. The damaged area of the skin is referred to as a lesion area. Skin lesions come in a variety of forms.The extracted features are given in figure 6.



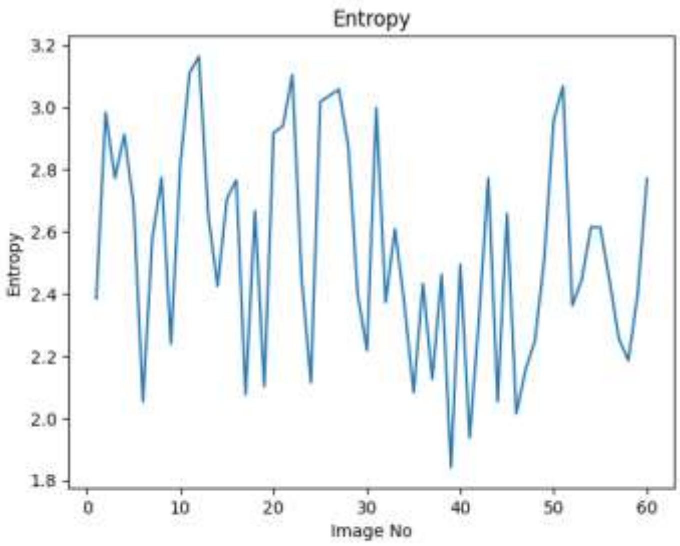


Fig. 6: Extracted features of Skin Image

Every lesion is divided into groups based on the particular kind of skin cells that gave rise to it. Melanocytic lesions, which resemble melanoma, are produced by melanocytes.

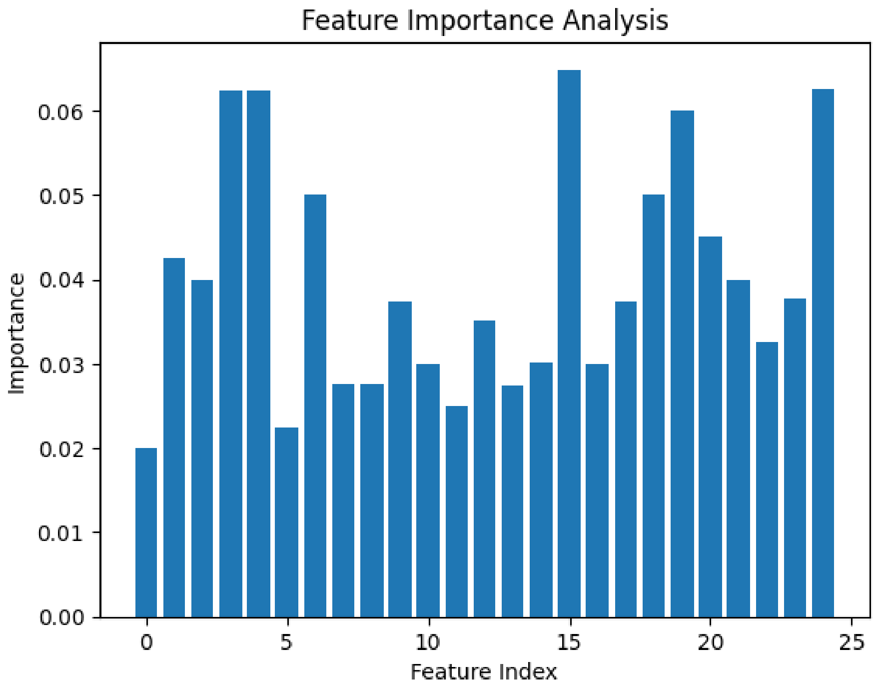


Fig. 7. Performance evaluation of skin based on various feature combination of skin based on various feature combination

The process of extracting features at multiple levels begins by utilizing the segmentation output. In this stage, characteristics such as intensity, statistical attributes, texture patterns, asymmetry, border details, edge structure, colour distribution, and lesion diameter are obtained. This figure 7indicates that texture directionality can be represented through statistical variations in pixel grey levels across multiple orientations.

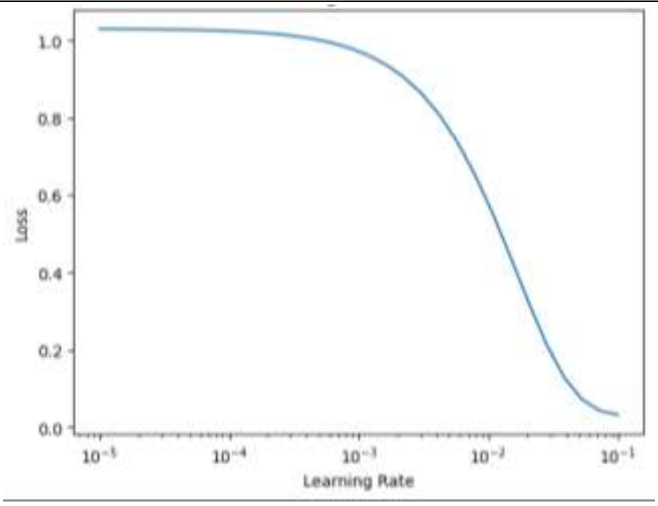


Fig. 8: Learning rate Vs Loss

The direction measure statistic was uniquely designed here to describe surface structure feature. By analysing the directionality of the image, it is possible to uncover higher-order statistical attributes of the texture. When applied to realistic textures, the recognition rate is significantly enhanced when applying high-level directional metrics. The image is divided into numerous directions using the direction measure, directional analysis is used to evaluate how the grayscale levels shift throughout the image. As a result of figure 8 this process, a quantitative response to the rate of change observed in the image pixels change in each direction is generated.

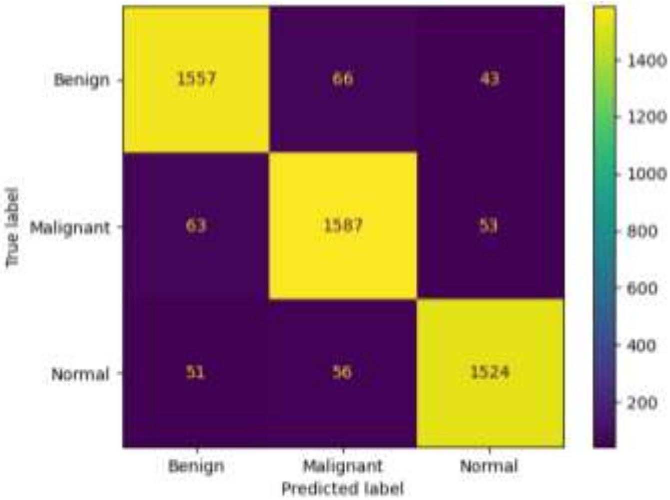


Fig. 9. confusion matrix

confusion matrix shown in figure 9, have the potential to save lives by offering an accessible, accurate, and reasonably priced method for early skin cancer screening. A variety of skin cell types, including squamous and basal cells, can cause non-melanocytic lesions. A number of dermoscopic features, including pigment network, can be used to visually distinguish between the two types of lesions.

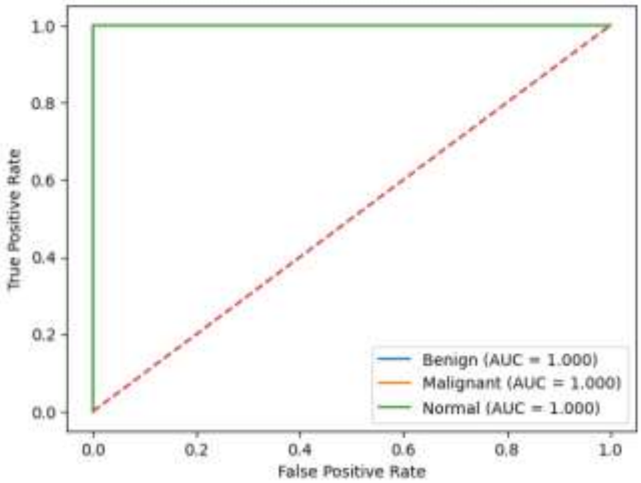


Fig. 10: Receiver Operating Characteristics plot

Figure 10 determine whether the lesion is benign or a malignant tumor. The lesion is categorized as one of the many skin lesions if it fits into the latter group. A number of dermoscopic characteristics are also considered in these evaluations. The primary clinical indicators of skin conditions such melanoma, seborrheic keratosis, and basal cell carcinoma are skin lesions.

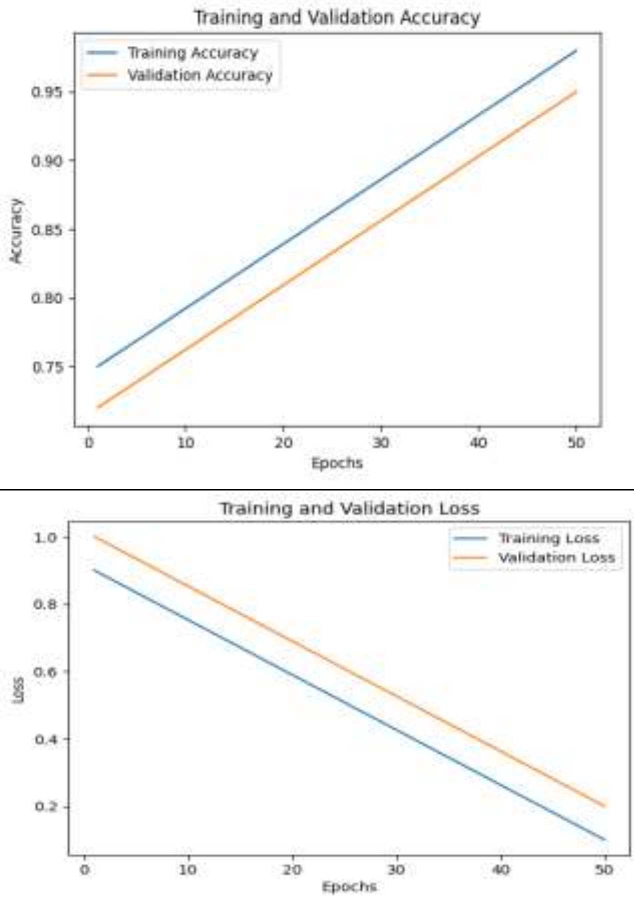


Fig. 11: classifiers accuracy and error comparisons

From figure 11 early detection of skin cancer is aided by computer-aided detection. The biopsy procedure is frequently used by medical experts to identify and diagnose a variety of disorders. The skin is removed or separated during the biopsy procedure, and these skin samples go through a battery of tests in the lab.

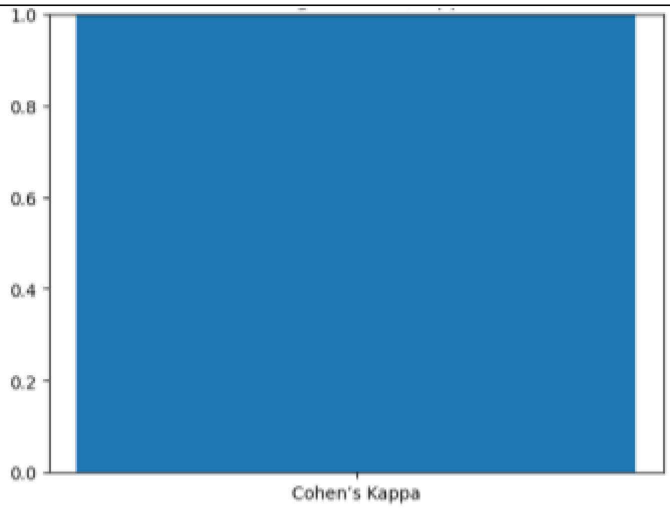


Fig. 12: classification result

Furthermore, Quantitative, visual, and surface pattern attributes are extracted using wavelet and co-occurrence matrix analysis. Lastly, this set of parameters is then employed to train a deep Q-learning network for categorizing diverse skin cancer types.

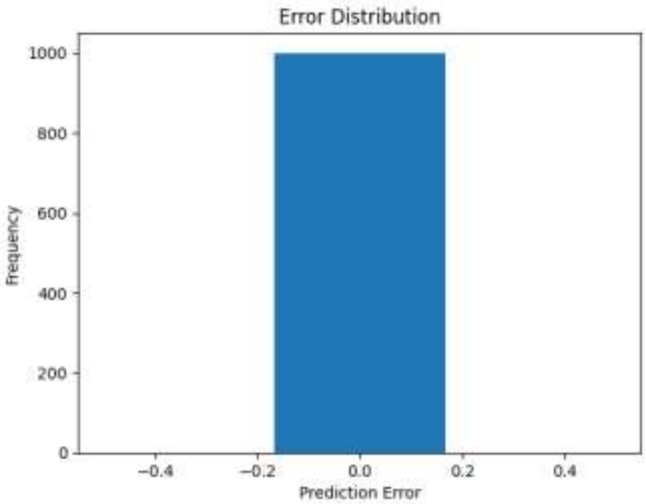


Fig. 13: Cross-entropies of training and validation

This work's primary benefit is its enhanced segmentation and classification capabilities. More advanced models for classifying disorders within themselves could be added to this work. Therefore, in order to extract the most intra-disease information, channel and spatial attention approaches will be used. Additionally, integrating graph neural networks can further boost the effectiveness and reliability of the entire process.

5. Conclusion

The number of skin cancer cases has significantly increased in recent years. By making screening tools accessible to the general public and democratizing access to them, open technologies that aid in lesion detection can help detect the disease in its early stages. The use of DL-based models is the main emphasis of this work. Additionally, the developed approach is implemented within flexible filters, primarily to eliminate hair interference. The results obtained with these proposed approaches are contrasted with those of the existing models that are documented in the literature. This article used transfer learning features to propose an enhanced system. A segmentation, Feature extraction, and classification method based on transfer learning was developed. This work's primary benefit is its enhanced segmentation and classification capabilities. More advanced models for classifying disorders within themselves could be added to this work. Therefore, in order to extract the most intra-disease information, channel and spatial attention approaches will be used. Moreover, incorporating graph network methodologies could improve the overarching system outcomes.Despite attaining the best performance, the accuracy-to-parameter ratio analysis showed one of the lowest efficiency ratios, demonstrating decreasing rewards with growing model complexity.

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