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# Impact of ultraviolet radiation on human skin owing to ozone depletion

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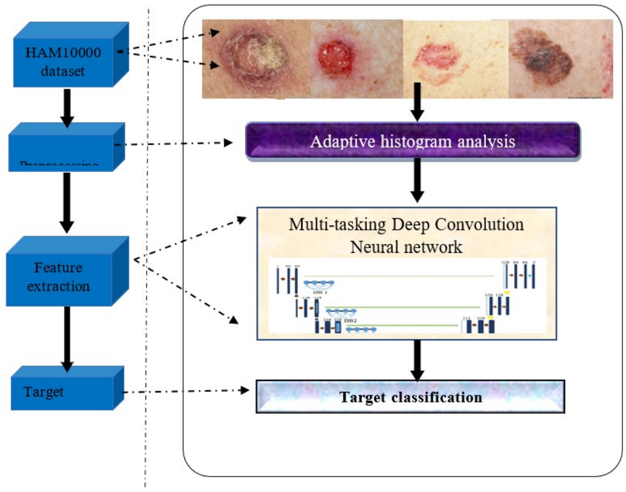
## Graphical abstract




## Abstract

Depletion of ozone molecules in the stratospheric layer surges the flow of ultraviolet (UV) rays on the surface of the earth. Generally, UV rays are the hazardous energy waves emitted from the sun that can cause acute and chronic effects on bio species. Exposure to UV rays in humans causes skin problems such as wrinkles, leathery skin, liver spots, actinic keratosis, and solar elastosis. It is also stated to be a basic premise for skin melanoma. Raising environmental pollution and natural disasters triggered the ozone depletion crisis into global criteria. The proposed work is developed with the intent to analyse the harmful effects of UV radiation on human skin. It detects the skin diseases raised due to UV rays and categorizes them based on chronic intensity using the convolution neural network. The deep learning network Multires U-Net is developed to classify acute and chronic UV skin lesions based on intensity. The proposed technique achieved 95% model accuracy in the testing and training process. Hence the proposed model has better efficiency in the detection of UV lesions.

**Keywords:** UV radiation, skin problems, ham10000 and uv dataset, pre-processing, and multires u-net classification

## 1. Introduction

Ultraviolet rays are the harmful energy waves of the sun that have a shorter wavelength range than visible light. UV rays reach the ground surface and cause a drastic effect on the human most prominently on the skin (Hamba 2021). The problems range from acute infections such as wrinkles, leathery skin, liver spots, actinic keratosis, and solar elastosis to chronic maladies like skin cancer, melanoma, keratitis, and cataracts (Zhou 2020; Manne 2020). On the other hand, trace exposure to UV rays contributes significantly to the synthesis of provitamin D, a crucial component of human health, as well as to the musculoskeletal system, atherosclerosis, and cognitive functioning (Kojima 2021). The presence of Ozone molecules in the upper atmospheric layer prevents the direct flow of UV waves into the earth's surface. Besides it absorbs about 97-99% of harmful ultraviolet radiation from the sun (Guo 2020). The evolutional activity of the human population and natural disasters trigger the emission of chlorofluorocarbons, hydrofluorocarbons, carbon tetrachloride, and methyl chloroform which tremendously destroy the ozone molecules (Passeron 2020). Depletion of the ozone promotes the penetration of harmful UV rays into the atmospheric layer of the earth (Todorova and Mandinova 2020).

The Effects of UV radiation is categorized under three classes based on the wavelength as UV-A (400nm - 315nm), UV-B (315 nm – 280nm) UV-C (280nm -100nm). With a longer wavelength, ultraviolet A (UVA) is allied to skin aging. UVB and UVC rays are significantly more energetic than UVA rays because they have a shorter wavelength (Hudson 2020). They are the primary cause for sunburns and skin cancer. The shorter wavelength causes greater effects on human skin than the longer wavelength (Ali 2021). Figure 1 illustrates the penetrating power of UV rays on skin. In recent days, UV effects had become a serious talk due the rising issue of ozone depletion. UV-B rays are observed in different regions of the world and people tremendously getting infected by various skin diseases (Banerjee 2020). Artificial Intelligence and neural network are the rapidly developing areas of healthcare and medical science contributes a lot in the prediction and therapy of all kinds of syndromes (Ozols 2021;Kassem 2021). The proposed work is developed with the intent to analyse the harmful effects of UV radiation on human skin. It detects the skin diseases raised due to UV rays and categorize them based on chronic intensity using the Multires U-Net. It predicts and classifies the acute and chronic skin diseases that develop due to UV exposure. It also forecasts the rise of skin diseases in the late period due to the penetration of UVA and UVB radiation in different regions of the world.

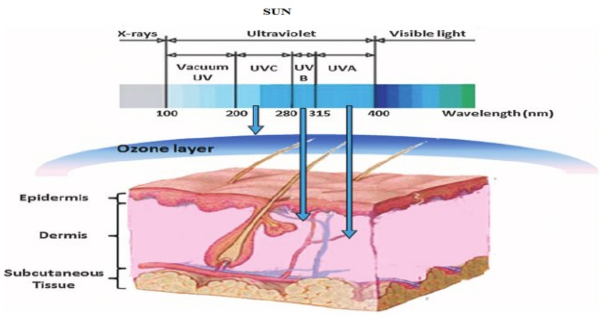



**Figure 1.** Penetrating wavelength of UV-A, UV-B and UV-C

The rest of the contents are regularized as follows; section 2 elaborates a brief description of related studies on UV radiation and skin problems. Section 3 put forward the concept and construction of proposed work. Section 4 enfolds the result and statistical analysis of UV effects on human skin. At last, section 5 holds the conclusion part of the proposed work.

## 2. Preliminary studies

Researchers have undergone several studies to detect the effects of UV rays on human skin. Through which, they put forward the harmful aspects of UV rays in healthcare. Some of that recent research is discussed in these retrospective studies and the techniques are explained and drawbacks are noted in the given section.

In 2015 King, L., Xiang, F., Swaminathan, A. and Lucas, R.M., has put forward an epidemiological study to measures the effects of sun exposures on skin. It measured the micro topography and UV auto fluorescence of sun exposure using some silicon casts. It analyses the level of population exposed to the UV exposure and measure the risk of skin disease over various latitudes. The measure was analysed in both individual and population level. The decision tree algorithm is used to measure the sun exposure. It states that there is no proper tool to measure the effect of UV radiation and its risk among human population (King 2015).

In 2017 Chakraborty. S *et al.,* has developed a concept analyse the dermatological problems caused by UV radiation due to the ozone layer depletion. Herein, they analysed the various risk factors raised owing to the ozone layer depletion. The objective was focused on the skin diseases such as melanoma, hyperplasia, sunburns and other minor skin problems. It concludes with state of developing an effective tool to diagnose and treat the skin cancer (Chakraborty 2017).

In 2019 Wang, H.H. *et al.,* has developed a deep learning tool to measure the skin non-melanoma skin cancer using nominating and medical records. The study collected dataset from 2 million sample patients from Taiwan. A convolution Network is developed to predict the risk factors of skin cancer using three chronological medical information of patients throughout a year. The study listed several limitations on datasets and medical information of patients (Wang 2019).

In 2021 Raksasat R. *et al.,* had put forward deep learning (DL) concept that forecasts the surface level of UV radiation for clinical application. This paper frames the significant aspects of UV radiation in clinical therapy. It used the UV dataset from Thailand. It categorised the surface UV and calculated the solar radiation. The biggest challenge of the network is training the DL networks due insufficient dataset (Raksasat 2021).

In 2021 Afza. F *et al.,* had developed a hierarchical super pixel DL network for classifying the Skin lesions. The framework is based on 2D super pixel image that is processed by fusing global and local enhanced images. The model used three step super pixel processing for segmentation and ResNet- 50 for classification. It shows some standard datasets for skin cancer classification (Afza 2021).

In 2021 Sultana, N., had designed a machine learning (ML) model to predict the sun protection step and control to prevent the skin cancer. The study began with random survey to assess sun protection manners. Later, ML model support vector machine and Artificial network to select the public sun protection practices. The performance is calculated with parameters like accuracy, precision and F1 score (Sultana 2021).

In 2021 Oh, S.T., Ga, D.H. and Lim, J.H., had developed a mobile DL technique for calculating the UV information (UVI) in particular location. The mobile DL are used for calculating the UVI values in user location. It measures the correlation of UVI and illuminance on natural light. The model works under mobile network and forecast the level of UVI in particular location in any condition (Oh ,2021).

The retrospective study on UV and its dermatological effects indicates that there is no proper study to detect the harmful effects of UV radiation in human skin. Moreover, it clarifies that deep learning models shows effective results over the prediction of UV related problems in medical aspects. Therefore, the proposed model is designed to using a deep learning model Multires U-Net to classify the acute and chronic inflammation of UV radiation. Section 3 put forward a detailed description of the Multires U-net in UVA and UVB

## 3. Proposed methodology

An increase in ozone layer depletion and surface UV radiation has turned out into a global issue as it affects the natural balance on the earth's atmosphere. It affects the climate, atmosphere, environment and all living species. It causes drastic effect human skin including wrinkles, leathery skin, liver spots, actinic keratosis, solar elastosis and even lethal type of skin cancer. The proposed work develops a deep learning network to classify the acute and chronic inflammation of UV radiation. The technique involves three steps data description, pre-processing and classification. Figure 2 shows the overall Block representation of proposed work.

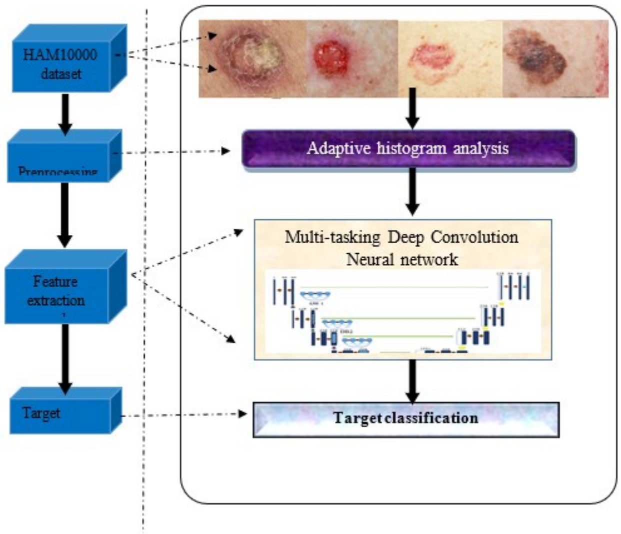



**Figure 2.** Overall Block diagram of the proposed model

### *3.1. Data Description*

DL training requires a large dataset for the training and testing process. In the present work, the dataset HAM10000 (Tschandl 2018) and the UV dataset were chosen.

### *3.2. Pre-processing*

Pre-processing is a significant process generally implanted in image processing to reduce noise distortion and ROI extraction. The contrast-enhanced adaptive histogram analysis is used in the proposed model to equalize the image. Image Contrast winch up the features of the skin lesions. To normalise and contrast the image, histogram equalisation is used. The images are sectioned into small blocks, and contrast is added effectively depending on the pixel intensity value. It raises the contrast of the surrounding region to achieve gh contrast.

$$B_m = \begin{cases} 1, & \text{if } ROI(a,b) = \text{location map}(m) \text{ and } ROI(a,b) = \text{location map}(n); \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

Where the Location Map (m) corresponds to the x-axis estimations of Correlation histogram and the Location Map (n) represents y-axis estimations of Correlation histogram.

$$\text{Correlation histogram} = \sum_{i=1}^{p}\sum_{j=1}^{q} CH_x\left(ROI\left(W_x\left(p_c\right)\right), POI\left(W_m\left(n_k\right)\right)+1\right) \quad (2)$$

Where $p_c$ be the center of pixel, $W_x$ be the windows $n_k$ denotes the eight neighbour pixels estimation of $CP$ where $k = 1,2,3 \ldots 8$. Then, the contrast enhance pre-processing image is Trained in the Multires U-Net architecture.

### *3.3. Multires DenseU-Net Architecture and Classification*

U-Net is an expanded structure of convolution neural network that designed to identify and classify the acute and chronic infectious area. In Skin infection, the infection mass vary enormously in shape, texture and structure and the mass are subtle, hard, rigid, and minute. Generally, the UV skin lesion appears as normal without any reaction and people often doesn't care about it. But this lesions spreads beneath the epidemic layers and cause serious trauma. The multi resolution dense u-net architecture has deeper feature segmentation efficiency in the medical field. It visualises and classify the medical images with high accuracy. A multi resolution dense u-net is designed in the work to significantly classify the acute and chronic skin lesions.

Prior to the concatenate process, U-Net performs four down samplings, resulting in resolution depletion. The subsequent resolution reduction demands extensional techniques that rely on a deep network structure to enhance accuracy. To overcome this process, a multires Dense U-net is designed (Figure 3).

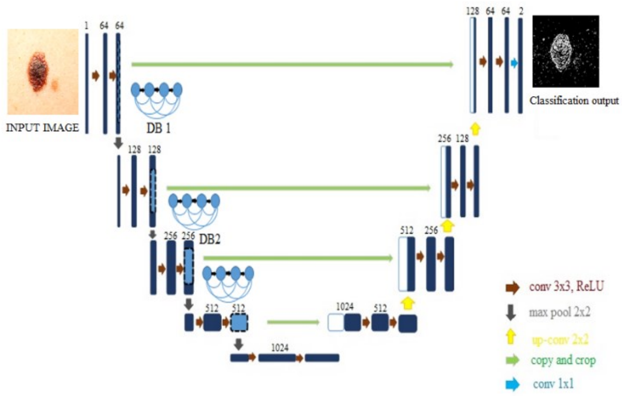



**Figure 3.** Proposed Multires Dense-UNet Architecture

### *Model architecture*

The U-net and dense convolution have been used to build the proposed network. The Dense-UNet is made up of two symmetrical paths: one for dense down sampling (left) and one for dense up sampling (right). To bind the two routes, several skip connectivity channels have been implemented.

The dense block implementation of U-net is shown in Figure 5. The convolution operation isolates background features in multiple scale through dense down-sampling path. The down- sampling layers extract subtle features and resolution is dropped to 128x128x3. To construct the dense U-net architecture the pooling and convolution operation is designed with dense down-sampling path. Here every layer is connected to the each other in a feedforward manner that reduce feature repetition. The proposed method is composed of 5 dense up-sampling layer and 5 dense down-sampling layer, as shown in

Figure 4. To perform the layer transformation, the transition block is provided. The dense block and merge operation is added in up-sampling layer to rebuilt the resolution as in Figure 4.

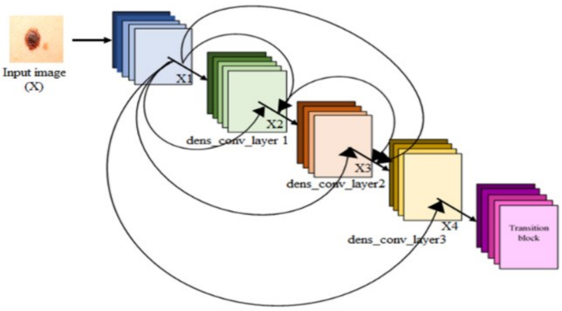



**Figure 4.** Flow chart of multires dense convolution layer

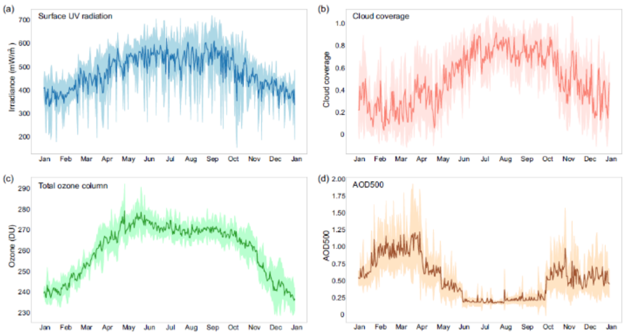



**Figure 5.** Surface UV radiation forecast over a year a) Irradiance of surface UV radiation, b) cloud coverage in a year, c) Total Ozone Column in a year and d) Annual AOD500

To be specific, there are 10 dense blocks layers, four transition block layers, four up-sampling layers, four merge layers, and one convolution operation in all, which includes ten dense blocks layers, four transition block layers, four up-sampling layers, four merge layers, and one convolution operation.

*Loss of function*

The loss function is typically the binary cross-entropy, which can be expressed as follows:

$$L = -\frac{1}{Z}\left(\sum_{k-1}^{l} n_k \log m_k + (1-n_k)\log(1-m_k)\right) \tag{3}$$

Where $Z$ denotes number of pixels, $n_k$ and $m_k$ denotes predicted valued and ground truth value respectively. However, owing to the high sensitivity of the cross-entropy loss function to imbalanced data, the resulting inefficient optimization involves the adaptive loss function. As a result, in our framework, Dice-loss is used as the loss function,

$$L = 1 - \frac{\sum_{k-1}^{l} n_k m_k + \partial}{\sum_{k-1}^{l}(n_k + m_k + \partial)} - \frac{\sum_{k-1}^{l}(1-m_k)(1-n_k) + \partial}{\sum_{k-1}^{l}(2 - m_k - n_k + \partial)} \tag{4}$$

Where $n_k$ defines predicted value and $m_k$ denotes the ground truth value.

## 4. Result and discussion

The Deep learning network designed in this system is implemented using a MATLAB2019. In result analysis, the UV skin lesions are trained in Multires dense U-Net architecture to classify the breast masses and output performance is calculated and its performance were analysed and compared with existing segmentation techniques. The comparison is calculated based on the variations between existing and proposed techniques.

### *4.1. Data description*

DL training requires large dataset for training and testing process. In present work, the datasets UV irradiance dataset in contiguous United States and HAM10000 is selected to train the different allergenic symptoms caused due to UV radiation.

Figure 5 deliberates the survey information that was conducted in solar irradiance of [18] to measure the exposure of UV radiation over particular region. It measures the irradiance exposure of surface UV radiation, cloud coverage over a year, annual ozone column and AOD500 measurement. It measures the amount of UV irradiance with ozone monitoring instrument during 2005 –2015. It calculated the daily dose of UV radiation (EDD) and shows that the UV irradiance increased about 0.5% over the year. It triggers skin allergies and skin cancer vulnerably.

### *4.2. Experimental result analysis*

Figure 6 gives the experimental analysis of result of proposed model throughout the processing stage. It deliberates the output result obtained in step process. The first step resembles the original dataset from the dataset. Second step is the pre-processed image of skin lesion in adaptive histogram analysis. Step 3 & 4 resembles the processing layer output of Multires U-Net. The Last step shows the experimental output that indicate the intensity of lesion.

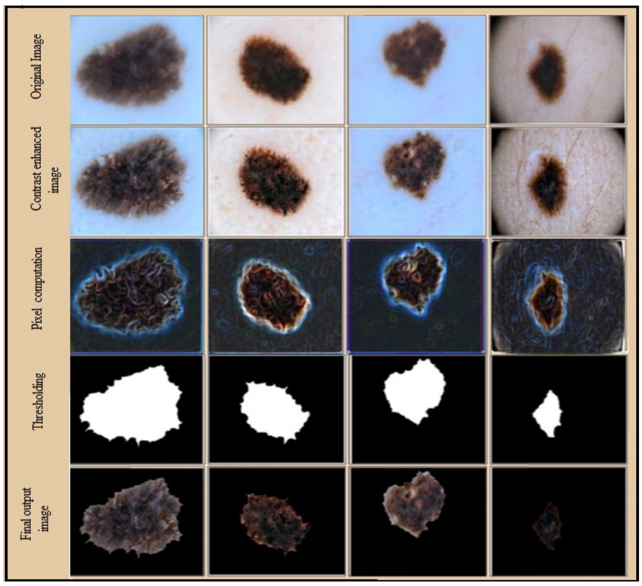



**Figure 6.** Experimental analysis of UV skin lesions using Multires U-Net architecture

### *4.3. Performance metrics*

The experimental results were evaluated with accuracy, specificity, sensitivity and DSI. The statistical evaluation of the parameters is given below,

$$Accuracy = \frac{true\,positvies\ + true\,negativies}{all\,samples} \tag{5}$$

$$Recall = \frac{TP}{TN + FN} \tag{6}$$

$$Specificity = \frac{TN}{TN + FP} \tag{7}$$

$$DSI\ = \frac{2 \times TP}{(TP + FP) + (TP + FP)} \tag{8}$$

$$f\,measure = 2\left(\frac{precision * recall}{precision + recall}\right) \tag{9}$$

Where, TP denotes the number of cases correctly identified as the patient, False positive FP denotes the number of incorrectly identified cases as the patient, True negative TN represents the number of correctly identified cases as healthy and False negative FN denotes the number of incorrectly identified cases as healthy.

### *4.4. Comparative analysis*

In comparative analysis, the performance metric parameters such as accuracy, specificity, Recall and Dice index. The parametric measurement is compared with the existing techniques to calculate the efficiency of the proposed Multires U-Net.

Table 1,2,3 and 4 represents the comparative analysis of the proposed Multires U-Net model performance with the existing technique such as ResNet, DenseNet and U-Net. Table 1 compares the accuracy performance of proposed model in detecting the acute and chronic cancer lesion. The comparative data is taken from the result of five randomly selected data. Table 2 compares the Recall performance of proposed model with existing baseline models. In Tables 3 and 4 the analysis is done to calculate the specificity and Dice index respectively. In above analysis, the obtained results shows that the proposed Multires U-Net model has remarkable results detecting the UV skin lesions.

**Table 1.** Comparative analysis of existing techniques with proposed Multires U-Net for Accuracy

| Image Fold no. | Accuracy | | | |
|---|---|---|---|---|
| | **ResNet** | **Dense Net** | **U-Net** | **Multi U-Net** |
| 1 | 0. 86 | 0.88 | 0.89 | 0.96 |
| 2 | 0.85 | 0.89 | 0.91 | 0.94 |
| 3 | 0.88 | 0.88 | 0.9 | 0.97 |
| 4 | 0.87 | 0.89 | 0.91 | 0.96 |
| 5 | 0.83 | 0.9 | 0.92 | 0.94 |
| Average | 0.8575 | 0.888 | 0.906 | 0.954 |

**Table 2.** Comparative analysis of existing techniques with proposed Multires U-Net for Recall

| Image Fold no. | Recall | | | |
|---|---|---|---|---|
| | **ResNet** | **Dense Net** | **U-Net** | **Multi U-Net** |
| 1 | 0.89 | 0.91 | 0.93 | 0.94 |
| 2 | 0.84 | 0.88 | 0.9 | 0.92 |
| 3 | 0.88 | 0.89 | 0.88 | 0.95 |
| 4 | 0.84 | 0.88 | 0.88 | 0.94 |
| 5 | 0.87 | 0.87 | 0.87 | 0.93 |
| Average | 0.864 | 0.886 | 0.892 | 0.936 |

**Table 3.** Comparative analysis of existing techniques with proposed Multires U-Net for Specificity

| Image Fold no. | Specificity | | | |
|---|---|---|---|---|
| | **ResNet** | **Dense Net** | **U-Net** | **Multi U-Net** |
| 1 | 0.88 | 0.94 | 0.95 | 0.96 |
| 2 | 0.89 | 0.9 | 0.9 | 0.94 |
| 3 | 0.86 | 0.86 | 0.94 | 0.92 |
| 4 | 0.87 | 0.87 | 0.92 | 0.94 |
| 5 | 0.9 | 0.9 | 0.93 | 0.91 |
| Average | 0.88 | 0.894 | 0.928 | 0.934 |

**Table 4.** Comparative analysis of existing techniques with proposed Multires U-Net for DSI

| Image Fold no. | DSI | | | |
|---|---|---|---|---|
| | **ResNet** | **Dense Net** | **U-Net** | **Multi U-Net** |
| 1 | 0.84 | 0.87 | 0.89 | 0.94 |
| 2 | 0.88 | 0.88 | 0.91 | 0.92 |
| 3 | 0.84 | 0.89 | 0.89 | 0.94 |
| 4 | 0.87 | 0.91 | 0.91 | 0.91 |
| 5 | 0.89 | 0.9 | 0.9 | 0.96 |
| verage | 0.864 | 0.89 | 0.9 | 0.934 |

Figure 7, shows the Graphical calculation of model accuracy that obtained in the testing and training process of proposed model.

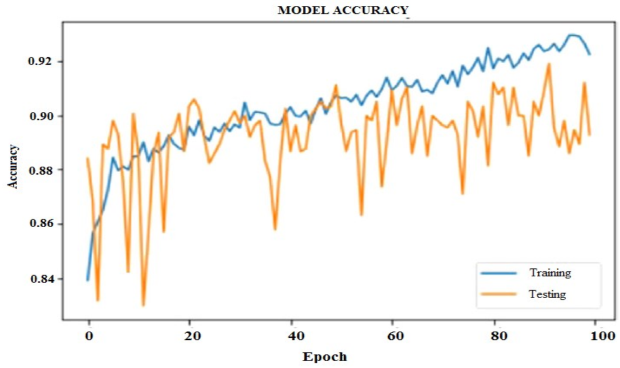



**Figure 7.** Model accuracy of testing and training Epoch

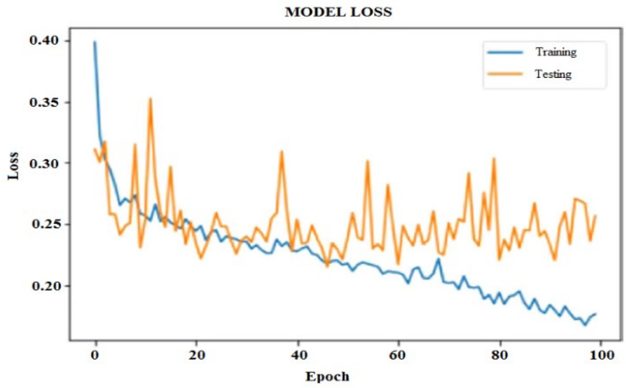



**Figure 8.** Loss Function of Proposed Model in Testing and Training Epoch

The Graphical representation Figure 7, indicates the model accuracy graph that obtain in training and testing process. Fluctuation of graph indicates the accuracy value of testing and training process. In accuracy, the testing and training graph line indicates the maximum accuracy achieved by the Multires U-net model for detecting the UV Skin lesions. Figure 8, shows the loss function acquired in the system during the testing and training process. The overall performance of the proposed systems shows that the proposed network has effective impacts in detecting the UV lesion and detecting its intensity. The intention of proposed work is to measures the harmful effects of UVB rays on Human. Study on UV irradiance insists that UV has several significant factors for bio and non-bio species in this world. It plays a major role in balancing the earth atmosphere. The risk factors that turn out this equilibrium state is human activity. Emission of Greenhouse gases and chemical substance in the earth's environment are the key elements that disturbs the natural balance, destroy ozone molecules and increase UV exposure. As the result, it causes numerous hazards to living species. We should definitely take measures to reconstruct these global issues and follows prevention steps in UV exposure region to control the extreme effects of UV radiation.

Figure 9, shows the Graphical calculation of F- measure that obtained in the testing and training process of Multires U-Net model performance with the existing technique such as ResNet, DenseNet and U-Net. The proposed technique performs well in terms of recall, specificity, precision, and accuracy based on the F measure.

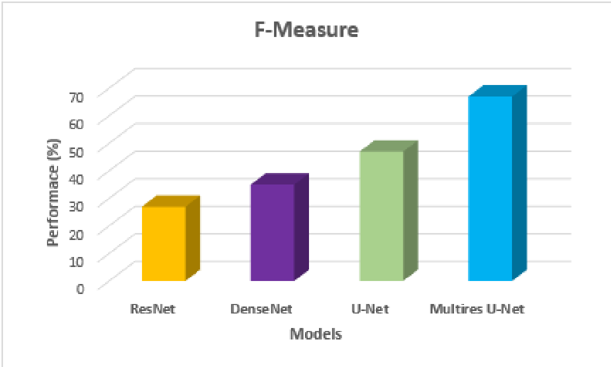



**Figure 9.** Comparison of F- measure of proposed and existing model

## 5. Conclusion

The proposed work focused on developing a deep learning tool that select and classify the chronic and acute UV skin lesion. The technique measures the intensity if the lesion to predict the acuteness. The UV dataset public available dataset for skin lesions and the HAM10000 dataset with 10000 skin images were selected to train and test the deep learning network. Initially, the dataset is process in adaptive histogram filters to remove the noise and increase the contrast in processing dataset. Later the dataset is directly fed into Multires U-Net for training and the network has 10 dense layers for up sampling, down sampling, transition and convolution. The network classifies the input data into features maps based on intensity and detect the acute and chronic UV lesions. The performance of the proposed model is calculated using the parameters such as accuracy, recall, specificity and DSI. Eventually the classification output of proposed model is compared with three different baseline techniques. The performance of the proposed model achieved about 95% accuracy in Multires U-Net model. In Future, the work can be extended with some robust network to achieve better evaluation. Probably the dataset should be considered from the appropriate region where the UV radiation cause high risk factor.

### Author contributions statement

The authors confirm contribution to the paper as follows: Study conception and design: P. Nagarajan, Durairaj Thenmozhi; Data collection: A. Jasmine Gnanamalar; Analysis and interpretation of results: A. Ahilan Appathurai; Draft manuscript preparation: P. Nagarajan, A. Ahilan Appathurai. All authors reviewed the results and approved the final version of the manuscript.

### Competing interests

This paper has no conflict of interest for publishing

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### Availability of data and material

Data sharing is not applicable to this article as no new data were created or analyzed in this Research.

**Human and Animal Rights**

This article does not contain any studies with human or animal subjects performed by any of the authors.

**Informed consent**

I certify that I have explained the nature and purpose of this study to the above-named individual, and I have discussed the potential benefits of this study participation. The questions the individual had about this study have been answered, and we will always be available to address future questions.

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