Enhanced Skin Cancer Detection Model: A Deep Learning Feature Fusion with Extreme Learning Machine Approach

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***Abstract*—A major global health concern is Melanoma, a Malignant form of skin cancer. This type of skin cancer is the most aggressive and has the highest fatality rate. An early diagnosis and course of treatment is crucial. With impressive results in numerous dermatological analytic tasks, deep learning approaches have made it easier to identify, segment, and classify skin lesions in the previous few years. In this present work, several deep learning and machine learning based techniques are used to classify Benign and Malignant skin lesions. The models we propose have been trained and assessed on a manually curated dataset, composed of Melanoma and Benign lesion images derived from HAM10000, a comprehensive benchmark dataset that includes a variety of skin lesion types. Further, some additional images are selected from Dermis.net, which consists of a wide range of dermatology information services on the internet. These images enhance variability in our dataset, and result in better generalization of the models. The proposed work achieves the highest accuracy of 98.0% for the validation set.**

***Index Terms*—Skin lesions, Melanoma, Deep learning, Transfer learning, Extreme Learning Machine**

I. Introduction

Skin cancers like Melanoma are characterized by their fast and invasive body-wide spread. Regardless of being fatal, research has revealed that it can be treated if diagnosed in its early stages. Individuals with fair skin, red or blonde hair, and blue eyes are more vulnerable to this variety of cancer. Moreover, individuals with higher exposure to sunlight and severe sunburns are more likely to contract this ailment. As a result, early diagnosis and treatment become essential [1].

Melanocytes, which are skin cells, are the origin of Melanoma. The dark pigment known as melanin, which gives skin its color, is fabricated by these cells. The majority of Melanomas have a color of black or brown. Very few have colors like pink, red, purple, or skin. Roughly 70% of instances of Melanoma emerge in healthy skin, with the remaining 30% emerge in an already-existing mole. It's vital to pay attention to any changes in the skin since most cases of Melanoma don't emerge with an existing mole. The probability of being infected with these skin lesions is greater in those over the age of fifty. Moreover, numerous keratoses lesions are likely to occur in those with a heredity of the condition. Darker skinned individuals have a reduced incidence of classic Seborrheic Keratosis. However, individuals with darker skin tones frequently experience dermatosis papulosa nigra, a variety of Seborrheic Keratosis. It is imperative to scrupulously diagnose Benign lesions and Melanoma in light of the formerly listed factors. To accurately categorize Benign lesions and Melanoma, we provide a variety of deep learning and machine learning techniques. Most of the medical professionals have come to the conclusion that excessive exposure to the sun is the main cause that leads to Melanoma, especially in children [9], [14].

In accordance to the data collected from statistics, UV radiation is responsible for 86% cases of Melanoma. These UV radiations released from the sun can alter specific genes that can influence how cells divide and grow by causing damage to a cell's DNA. And when the DNA of the human skin is harmed by these radiations, the cells present in them begin to proliferate and as a result consequences arise.

On the other hand, Benign skin lesions are usually Benign and not Malignant in nature. Since these skin lesions are nothing but aberrant skin growths, no extra care is required for them. A few typical instances of Benign skin conditions are birthmarks, moles, freckles, skin tags and acne. Recently, research indicates that individuals with diabetes may have high risk of getting affected by skin cancer, possibly due to underlying biological mechanisms. Skin cancer, diabetes [11], and breast cancer [6]. are all distinct medical conditions, but machine learning studies have revealed potential connections among them [10], [5].

Seborrheic Keratosis is a Benign skin growth that is quite common and often resembles a mole. It's frequency generally rises with the age of a person and they are common between the ages of 20 and 45. Most individuals encounter it at least once in their lifetime. Normally they pose no hazard and don't need to be treated, however they can be treated according to the wishes of the patient. Another term for skin growths is epidermal tumor. On the skin's outer layer called as the epidermis, this tumor occurs as a collection of extra cells. But they aren't thought to be a risk factor for skin cancer. Seborrheic keratoses is a kind of Keratosis lesion, which are round or oval-shaped skin patches that often look "stuck on." They can easily be felt with your finger even when they are flat because they are elevated above the skin. They can be brown, black, tan, or, less frequently, pink, yellow, or white. They generally show up in large groups. The likelihood of developing these skin lesions is greater in people above the age of fifty. Furthermore, these keratoses lesions are likely to occur in those people who have a family history of this condition. Darker skinned individuals generally have a lower incidence of classic Seborrheic Keratosis. Nonetheless, individuals who have darker skin tones mostly experience dermatosis papulosa nigra which is a kind of Seborrheic Keratosis.

Our suggested approach employs ResNet50, a Residual Neural Network variation, and a Deep Convolutional Neural Network. Using the dataset, each network is trained independently, using 0.001 as the learning rate and Adam optimizer. Support Vector Machines get the features after they have been collected from both networks and given to them. It is discovered that with relatively little training time, Support Vector Machines produce noteworthy outcomes. Extreme Learning Machine (ELM) is trained using the combined features to further refine the outcomes. The results show that, out of all the strategies, Extreme Learning Machine produces the best outcomes. Examined on 200 Melanoma and 200 non-Melanoma pictures, it reaches the greatest accuracy of 98.0%. According to their suggested model, 97% accuracy is the best available.

The subsequent part of the document is organized in the following manner: Section II encompasses a review of relevant literature, Section III discusses proposed methodology, Section IV offers an in-depth examination of the findings and their discussion, and Section III presents the results and proposes possible conclusions along with directions for future research.

II. Related works

The dermatology sector has seen considerable progress in recent times, driven by the adoption of deep learning methods for identifying and diagnosing skin cancer. These techniques use deep learning architectures, such as Convolutional Neural Networks (CNNs), to evaluate dermatological images with exceptional efficiency and accuracy. In this section, we review the existing literature on skin cancer detection utilizing deep learning methods, highlighting the key approaches, methodologies, and findings.

Gerald et al. [9] presented an ensemble model for detection of Melanoma in which the class imbalance is resolved using multiple classifier system, which involves border detection using JSEG (J segmentation) and feature extraction. It uses a neural network fuser to combine classifiers trained on balanced subspaces and it uses 564 skin lesions (from 3 university hospital) resulting in an accuracy of 93.83%.

Lei et al. [1] presented a model to detect the lesion is Melanoma or non - Melanoma by using multi - scale lesion biased (MLR) to extract detailed skin lesion characteristics and joint reverse classification (JRC) to more effectively differentiate between Melanoma and non-Melanoma lesions. It uses PH2 dataset and obtained 92.00% accuracy.

Zahra et al. [14] presented a model that employs color and texture extraction methods to construct a 13-dimensional feature vector, consisting of four texture features and nine color features, and utilizes a Support Vector Machine to identify Melanoma from other types of dermoscopic pictures. It uses PH2 dataset and is able to achieve a highest accuracy of 96%.

Fatma et al. [12] presented a CNN model to identify skin lesion as Malignant and Benign. They have used images from ISIC 2018 Challenge dataset which is a publicly available dataset. The presented model was trained using 350 images of each class from the dataset. The model attained an impressively high accuracy rate of 96.67% with a learning rate of 0.001.

Firoz et al. [15] presented a new model which uses Multi direction 3D CTF extraction to compute color as a single feature and BPNN is used to identify Malignant and non-Malignant images. It uses PH2 dataset which consists of 160 Benign and 40 Melanoma images. The best accuracy given by their proposed model is 97%.

III. Proposed methodology

A. Overview

We propose a deep learning based technique involving Extreme Learning Machine (ELM) which utilizes the learned features from a deep Convolutional Neural Network and ResNet50, a variant of Residual Network with frozen weights, to distinguish Malignant and Benign skin lesions from dermatoscopic images. Our proposed model is trained on a manually prepared dataset, consisting of Malignant and Benign dermatoscopic images from HAM10000 with some additional high quality images from dermis.net. The proposed model achieves the highest accuracy of 98.00% and performs better than other techniques employed by us.

B. Datasets

Our proposed approach makes use of dermatoscopic images from the HAM10000 dataset, a reputable publicly accessible dataset of dermatoscopic images from various sources, including common pigmented skin lesions like Benign and melanocytic lesions. [13] [2]. Further, to expand the diversity of dataset and to enhance the generalizability and robustness of our methodology, some additional high quality dermatoscopic images are taken from dermis.net, which basically is the wide-ranging dermatological information service accessible on the web. It provides elaborate image collection, complete with diagnoses and differential diagnoses, case reports and added information on nearly every skin ailments. [3].

TABLE I
DATASET DISTRIBUTION

CLASS NAME	TRAIN IMAGES	VALIDATION IMAGES
Melanoma	800	200
Benign	800	200

Our proposed work uses 600 Melanoma images from HAM10000 dataset and additional 400 Melanoma images from dermis.net. 1000 Benign images are taken from HAM1000 dataset. Out of 1000 images in each class, 200 images are taken for validation purposes and remaining 800 images are utilised for training purposes, leading to 80:20 split for training and validation for an individual class. Table I represents the dataset distribution. Fig 1 shows some of sample images from the dataset used in our proposed work.

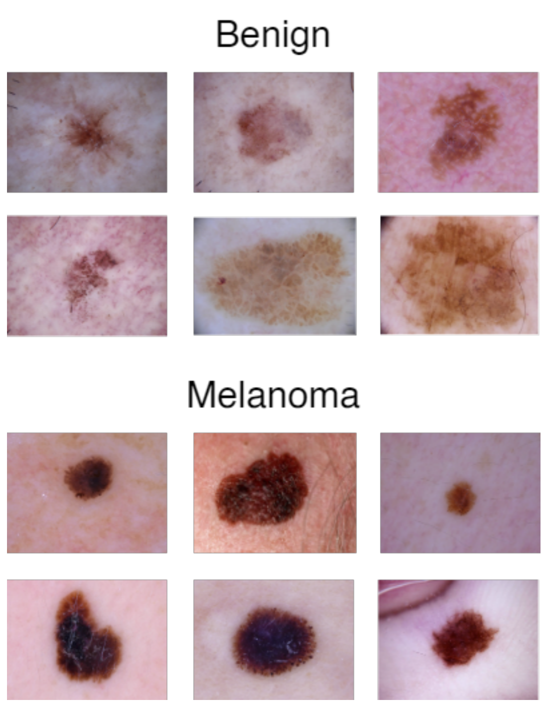

Fig. 1. Example images from the dataset

C. Pre-processing

The procedure of pre-processing images is crucial in enhancing the robustness of the models. Most of the dermatoscopic images comprise of noise and artifact which have to be removed or reduced before training the models. To remove the hair and other noise from the dataset, we utilised a step-by-step procedure. The images are first converted to grayscale, and morphological operations and black hat transformations are performed on them. The black-hat transformed images are then thresholded to create binary masks. The final step involves inpainting the original images with the binary masks to remove hair and other noise from the images. Fig 2 illustrates the above mentioned pre-processing steps.

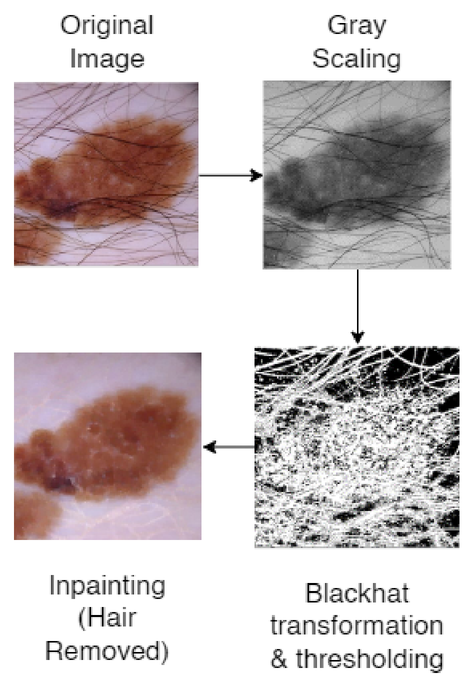

Fig. 2. Noise removal steps

In addition to pre-processing, different augmentation techniques are used to increase the quality and diversity of the dataset, and also to enhance the performance of the proposed methodology. Techniques like random rotation, random flipping and random brightness are used for image augmentation.

The dermatoscopic images are then resized to small image size of 224 x 224 pixels. The images pixel values are normalized for data centring and fast computing.

D. Convolutional Neural Network

The generated training dataset consisting of 1600 dermatoscopic images is used to train a deep Convolutional Neural Network [7]. After the training phase, the network was evaluated using a validation dataset that consisted of 400 images. The network uses Adam for optimization and Binary Cross Entropy as its loss function. The Sigmoid activation function is applied in the output layer, whereas the Rectified Linear Unit (ReLU) activation function is implemented in the intermediate layers. Default learning rate of 0.001 is used. Accuracy is used as metrics while training the CNN model for 15 epochs. Reduce LR on Plateau callback is used while training this network. The function's parameters are configured to Reduce the learning rate by 50% if the validation accuracy fails to improve for two consecutive epochs. Network performance is improved and over-fitting is prevented by using several Dropout and Batch Normalization layers. The CNN model gives accuracy of 96.50% with training loss of 0.1118. The CNN model takes approximately 15012 seconds for training.

E. Residual Neural Network

A deep Residual Network – ResNet50 is employed and trained on the training dataset with frozen weights. Analogously to the Convolutional Network, training is conducted at a learning rate of 0.001 using Adam as the optimizer. The network is trained for 10 epochs. A dense layer with sigmoid activation function is used as output layer. The ResNet model gives accuracy of 96.50% with training loss of 0.1374. It takes approximately 7027 seconds for training.

F. Support Vector Machine

In the Convolutional Neural Network and Resnet50, the final layer is replaced by a dense layer that consists of 512 neurons and utilizes a linear activation function. The features are extracted from the updated Convolutional Neural Network and Resnet50, which are of the shape (None,512). These features from both the networks are then combined using simple mathematical average operation such that the resultant features of the shape (None,512) consist of learning from both the networks. These features are passed to Support Vector Machines (SVM) with linear kernel. The Support Vector Machine gives an appreciable result, with accuracy of 96.5%. The SVM model requires approximately 7 seconds for training.

G. Proposed Extreme Learning Machine

To surpass the results obtained by Support Vector Machines, Extreme Learning Machine [8], [4] is used. The combined features are used to train Extreme Learning Machine (ELM) with hidden layer size of 256 [6]. The random state is set to 42 and the maximum number of iterations to 1000 with Rectified Linear Unit (ReLU) as the activation function. Upon evaluation with the validation dataset, the ELM model was found to achieve the highest accuracy at 98.0%, outperforming all other techniques we implemented. It correctly classifies 392 validation images out of total 400 images. The proposed model requires approximately 304 seconds for training. The Fig 3 illustrates all the steps involved in the proposed model.

IV. RESULTS

The proposed deep learning based methodology which utilizes Extreme Learning Machine (ELM) with combined features from CNN and ResNet50 when evaluated on the validation dataset, gives the highest accuracy of 98.00%. The experimental outcomes are accessed on an online Python 3.10.12 environment, utilizing 29GB RAM with NVIDIA

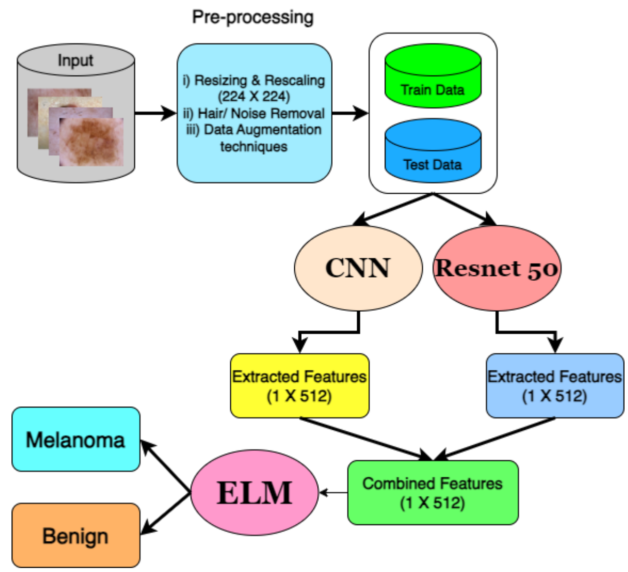

Fig. 3. Proposed Methodology

Tesla T4 GPU. Numerous metrics, including accuracy 1), precision (2), recall (3), f1 (4) score, area under ROC, training time and training loss have been used in a thorough evaluation of the proposed work, where True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) are the associated terms.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 = \frac{2 * precision * recall}{precision + recall} \tag{4}$$

To attain the best outcomes, particular hyper-parameters have been selected, as detailed in the Table II. The proposed model is evaluated on different classifiers like CNN, ResNet50, and SVM, as shown in Table III. When assessed with metrics such as Precision, Accuracy, F1 score, and Recall, the proposed Extreme Learning Machine classifier outperforms the comparative classifiers. Fig 6 displays the progression of training and validation loss for the constructed Convolutional Neural Network and ResNet50, at each epoch throughout the training period. It is observed that ResNet50 has a very smooth curve, whereas in case of CNN the loss reduces significantly after a few epochs, and after that only small reduction in the loss is noticed. Fig 4 depicts the ROC curve and it's area, of different classifiers employed in this study. ROC or Receiver Operating Characteristic Curve is one of the pictorial representation of performance in binary classification. It is plotted using True Positive Rate (TPR) (5) and False Positive Rate (FPR) (6) of the classifier at different threshold values.

$$TPR = \frac{TP}{TP + FN} \tag{5}$$

$$FPR = \frac{FP}{FP + TN} \tag{6}$$

Fig. 5 shows the confusion matrix of the best classifier - Proposed ELM with combined features from CNN and ResNet50. Confusion Matrix is a widely used evaluation method which shows the performance of the classifier by displaying the number of accurate and inaccurate predictions performed by the classifier. The ELM classifier correctly classifies 392 images from the test dataset consisting of 400 images. Table IV shows the comparison of our proposed work with the literature. Fig. 8 shows some of the sample predictions made by the proposed model. The proposed model gives very good real-time predictions in classifying Melanoma and Benign skin lesions. It is observed that the proposed model gives approximately 9 correct predictions when tested on 10 random dermatoscopic images. Fig. 7 is the graphical representation of reduction in training loss of the proposed model - ELM at different iterations during training.

TABLE II
HYPER-PARAMETERS OF THE PROPOSED MODEL

NAME	VALUE
Hidden layer size	256
Activation function	**ReLU**
Max. iterations	1000
Random state	42

TABLE III
COMPARATIVE ANALYSIS OF THE PROPOSED MODEL AGAINST VARIOUS CLASSIFIERS

METHOD	ACCURACY	PRECISION	RECALL	F1 SCORE
CNN	96.50%	96.50%	96.50%	96.50%
ResNet50	96.50%	96.50%	96.50%	96.50%
SVM	96.75%	97.46%	96.0%	96.72%
ELM(proposed model)	**98.00%**	**98.00%**	**98.00%**	**98.00%**

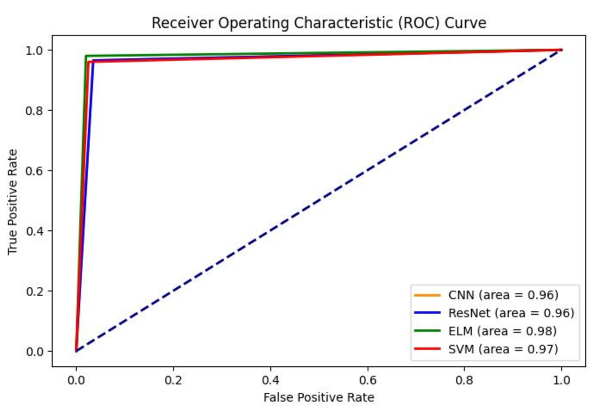

Fig. 4. ROC CURVE COMPARISON OF THE CLASSIFIERS

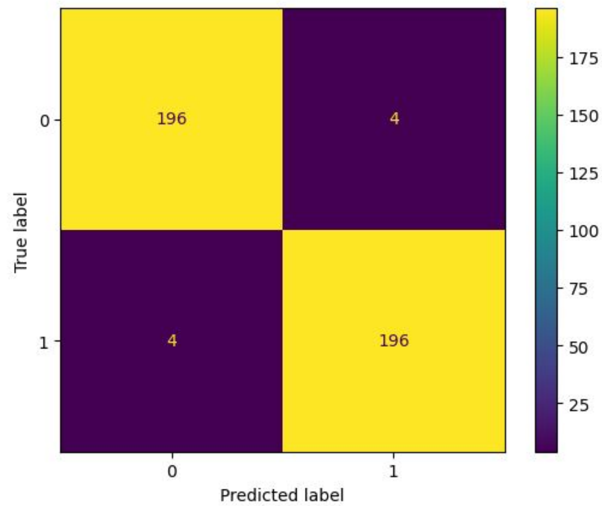

Fig. 5. CONFUSION MATRIX OF THE PROPOSED ELM MODEL

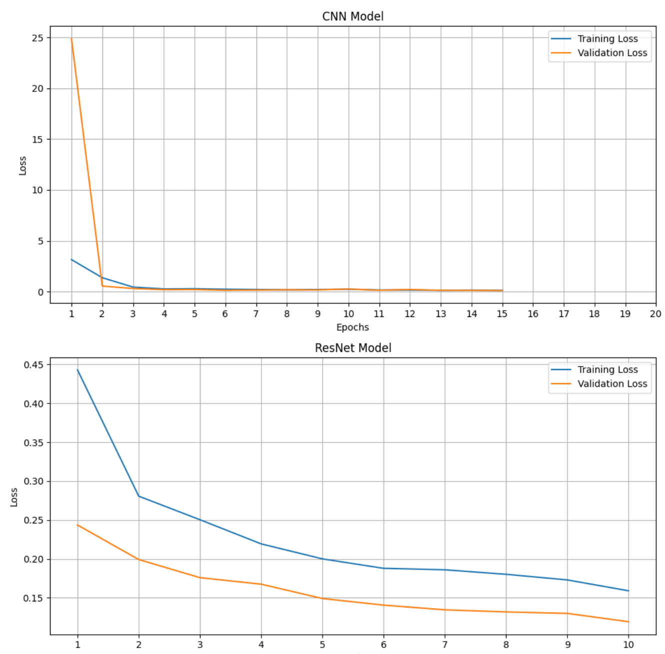

Fig. 6. TRAINING AND VALIDATION LOSS CURVE OF CNN AND RESNET50

TABLE IV
COMPARISON OF THE PROPOSED METHODOLOGY WITH THE LITERATURE

STUDY	ACCURACY (%)
Lei et al. [1]	92.00%
Gerald et al. [9]	93.83%
Zahra et al. [14]	96.00%
Fatma et al. [12]	96.67%
Firoz et al. [15]	97.00%
CNN + ResNet50 + ELM (Proposed Model)	**98.00%**

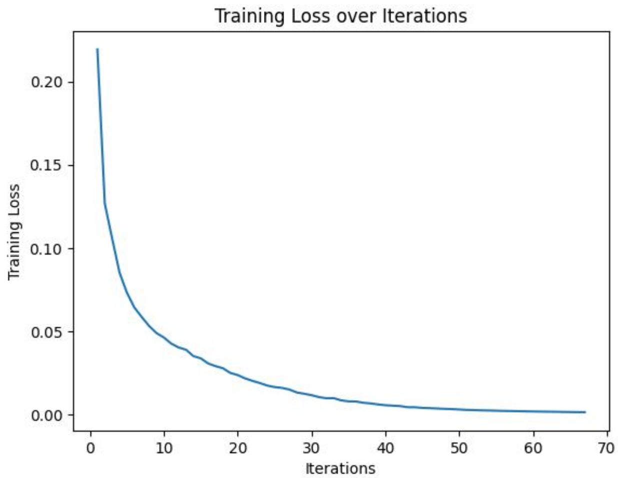

Fig. 7. TRAINING LOSS CURVE OF THE PROPOSED MODEL

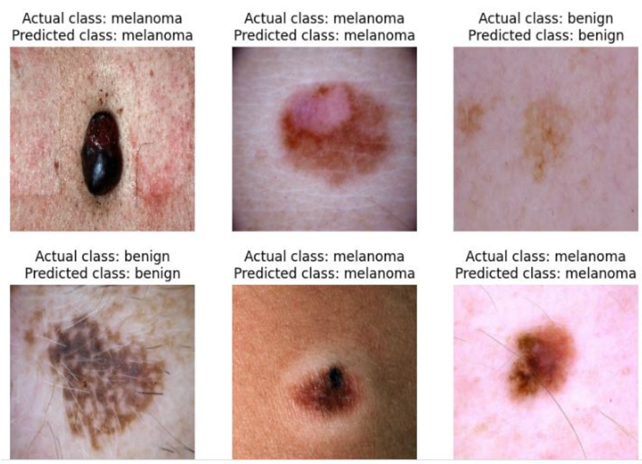

Fig. 8. EXTREME LEARNING MACHINE MODEL SAMPLE PREDICTIONS

V. CONCLUSION AND FUTURE SCOPE

In our study, which aimed at classifying Malignant and Benign skin lesions from dermatoscopic images, we explored multiple deep learning and machine learning techniques like CNN, ResNet, SVM, ELM. By combining the features extracted from CNN and ResNet50 and feeding them into ELM classifier, we were able to improve our results. The ELM classifier exhibits superior performance across metrics such as Precision, Accuracy, F1 score, and Recall, and it also delivers accurate predictions upon image evaluation. Moreover, it performs better than other traditional classifiers. In the future, we hope to improve the state of skin disease identification and classification by expanding our dataset with more diverse photos of skin lesions and by researching new techniques.

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