THE 15th INTERNATIONAL CONFERENCE ON COMPUTING, COMMUNICATION AND NETWORKING TECHNOLOGIES (ICCCNT 2024)

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

By:

Parekh Ved Hemantkumar

Biswajeet Samal

Rudra Narayan Panda

Sk. Shahid Akhtar

Debendra Muduli

Santosh Kumar Sharma

C.V Raman Global University, Bhubaneswar, Odisha

Outline

- Introduction
- Objective
- Related Work
- Research gap
- Proposed Methodology
- Result and Discussion
- Conclusion & Future Work
- References

Introduction

- Melanoma is a kind of skin cancer known for its fast and invasive spread throughout the body.
- Early detection of melanoma is vital for treatment.
- Individuals with higher exposure to sunlight and severe sunburns are more vulnerable to this disease.
- Moreover, people with fair skin, blonde hair and blue eyes have more chances of getting affected by this disease.
- Deep Learning and Machine Learning approaches have made it easier to identify and classify skin lesions, resulting in advancement of biomedical sciences.

Objective

- The objective of the paper is to develop a highly accurate and efficient methodology for the classification of Melanoma and Benign skin lesions by leveraging a combination of Convolutional Neural Networks (CNN), ResNet50, and Extreme Learning Machine (ELM).
- The proposed model, evaluated on the HAM10000 dataset and additional images from Dermis.net, achieved a significant accuracy of 98.00%

Related Work

- Gerald et al. [10] presented an ensemble model for detection of melanoma in which the class imbalance is resolved using multiple classifier system, which involve 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. [15] 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%.

Research Gap

- The comparative analysis with the literature reveals that, our approach performs better than the others.
- Our approach involves an unique technique of feature extraction and feature fusion.
- The variation of Feature Fusion is applied in less of the research work.
- So, in our proposed model, we have trained ELM on the learned features from CNN and Resnet-50 which outperforms the other models in our literature review.

Proposed Methodology

A. Overview

- We propose a deep learning technique involving Extreme Learning Machine (ELM) which utilizes the learned features from Convolutional Neural Network and Residual Network (ResNet50) to distinguish Melanoma and Benign skin lesions.

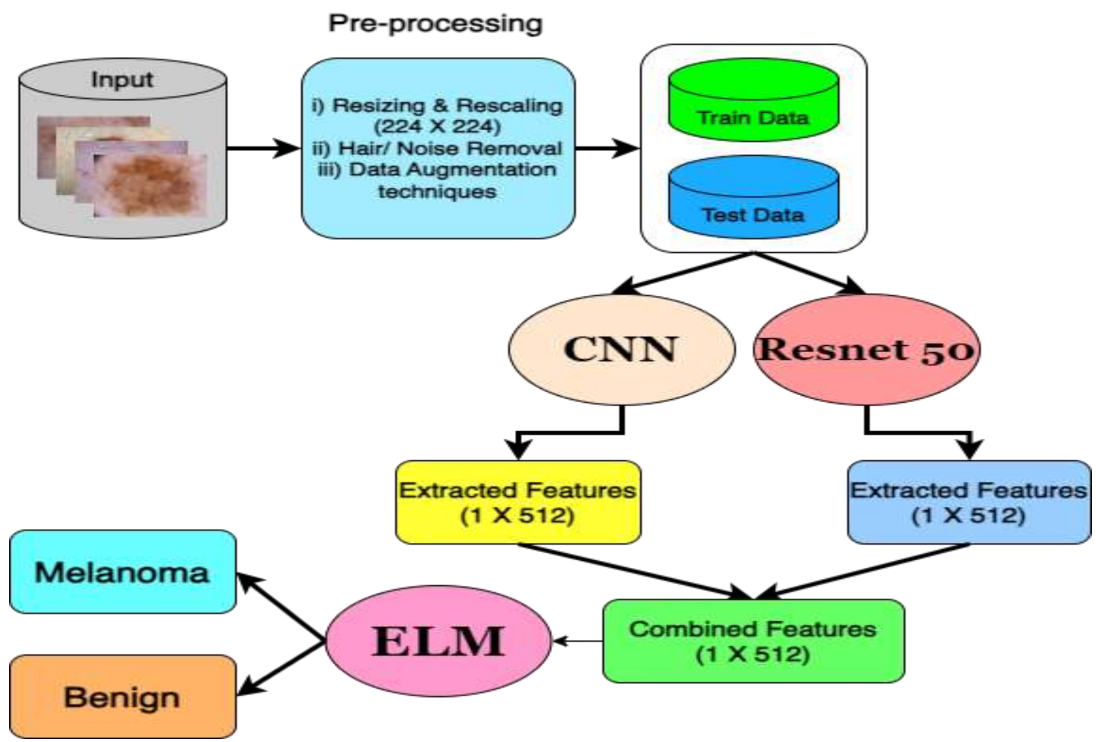

Fig. 01 – Proposed Methodology

Proposed Methodology

B. Dataset

- In deployed scheme we have utilized one standard dataset named HAM10000 [13].
- The HAM10000 dataset contains approximately 10000 images broadly classified into malignant and benign.
- To increase the diversity of the melanoma class and generalizability of the models, additional high quality images are taken from dermis.net
- Dermis.net is the wide-range dermatological information service available on the web.

- Melanoma - 600 images from HAM10000 + 400 from dermis.net
- Benign – 1000 images from HAM10000

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

Table 01 – Dataset distribution

Proposed Methodology

B. Dataset

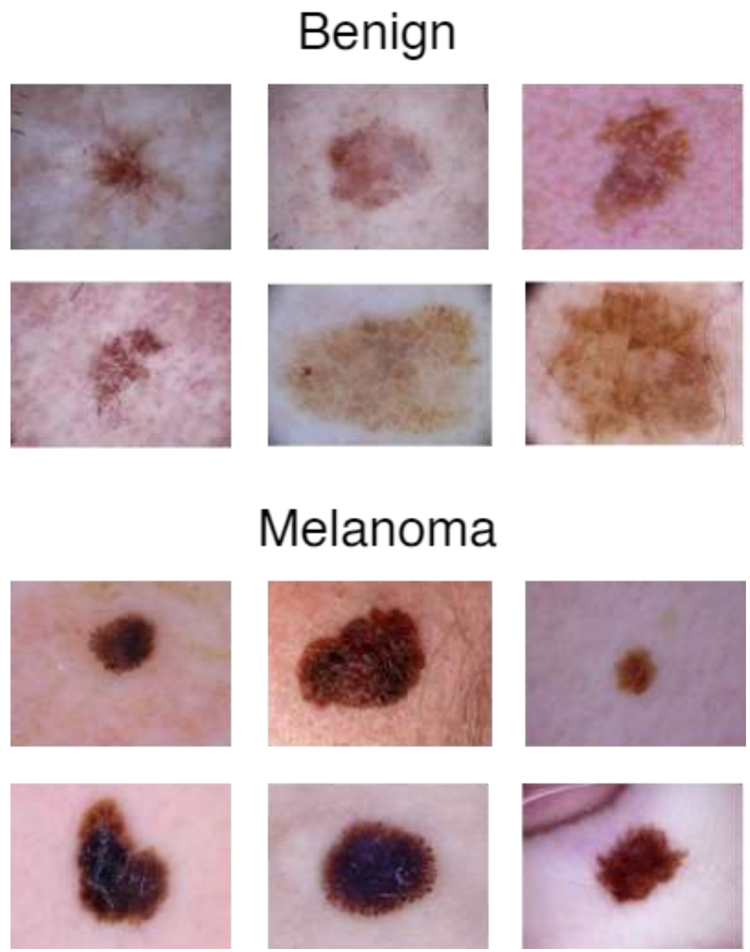

Fig. 02 – Example images from the dataset

Proposed Methodology

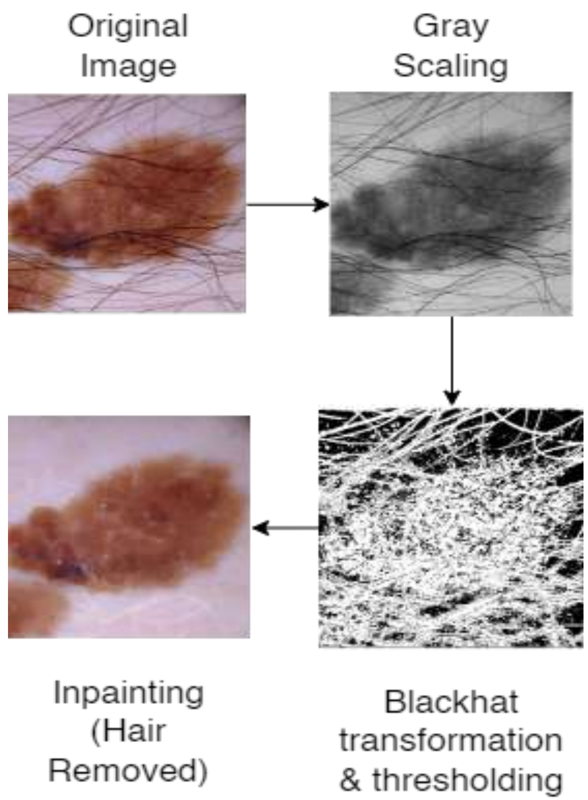

Fig. 03 – Example images from dataset

C. Pre-processing

- ❖ Most of the dermatoscopic images comprise of noises, which is required to be removed.
- ❖ Hair and noise removal steps employed in this work is as follows:
  - I. Gray scaling
  - II. Black Hat transformations
  - III. Thresholding
  - IV. Inpainting
- ❖ Augmentation techniques:
  - I. Random rotation
  - II. Random flip
  - III. Random brightness
- ❖ Resizing – 224 x 224 pixels
- ❖ Normalization for fast computing

Proposed Methodology

D. CNN

- A customized deep Convolutional Neural Network is trained using the prepared dataset, consisting of 1600 training images.
- Optimizer – Adam
- Loss function – Binary Cross Entropy
- Output layer activation function – Sigmoid
- Callback – Reduce Lr on plateau
- Epochs - 15

E. ResNet-50

- ResNet-50, a variant of Residual Neural Network is trained on the prepared dataset, with frozen weights.
- Optimizer – Adam
- Loss function – Binary Cross Entropy
- Output layer activation function – Sigmoid
- Callback – None
- Epochs - 10

Proposed Methodology

Feature fusion – SVM & ELM

- The final layer of CNN and ResNet50 is replaced by a dense layer of 512 neurons with linear activation function.
- The features are extracted from both these models, which are of the shape (None,512)
- These features are combined to get the resultant feature of shape (None,512), which represents the learnings from both the models.

- The combined feature is then passed to Support Vector Machine with linear kernel.

- Moreover, the features are also passed to Extreme Learning Machine separately, with 1000 iterations and ReLU as the activation function.

Results and Analysis

Table 02 – Hyper parameters of the proposed model

Name	Values
Hidden Layer Size	256
Activation Function	Relu
Max. Iteration	1000
Random State	42

Evaluation metrics:

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

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

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

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

Results and Analysis

Table 03 - Comparative analysis of the proposed model against various classifiers

Model	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	96.00	96.72
ELM(Proposed Model)	**98.00**	**98.00**	**98.00**	**98.00**

Table 04 - Comparative result analysis with the literature

Study	Accuracy (%)
Lei et al.	92.00
Gerald et al.	93.83
Zahra et al.	96.00
Fatma et al.	96.67
Firoz et al.	97.00
CNN+ResNet50+ELM(Proposed Model)	**98.00**

Results and Analysis

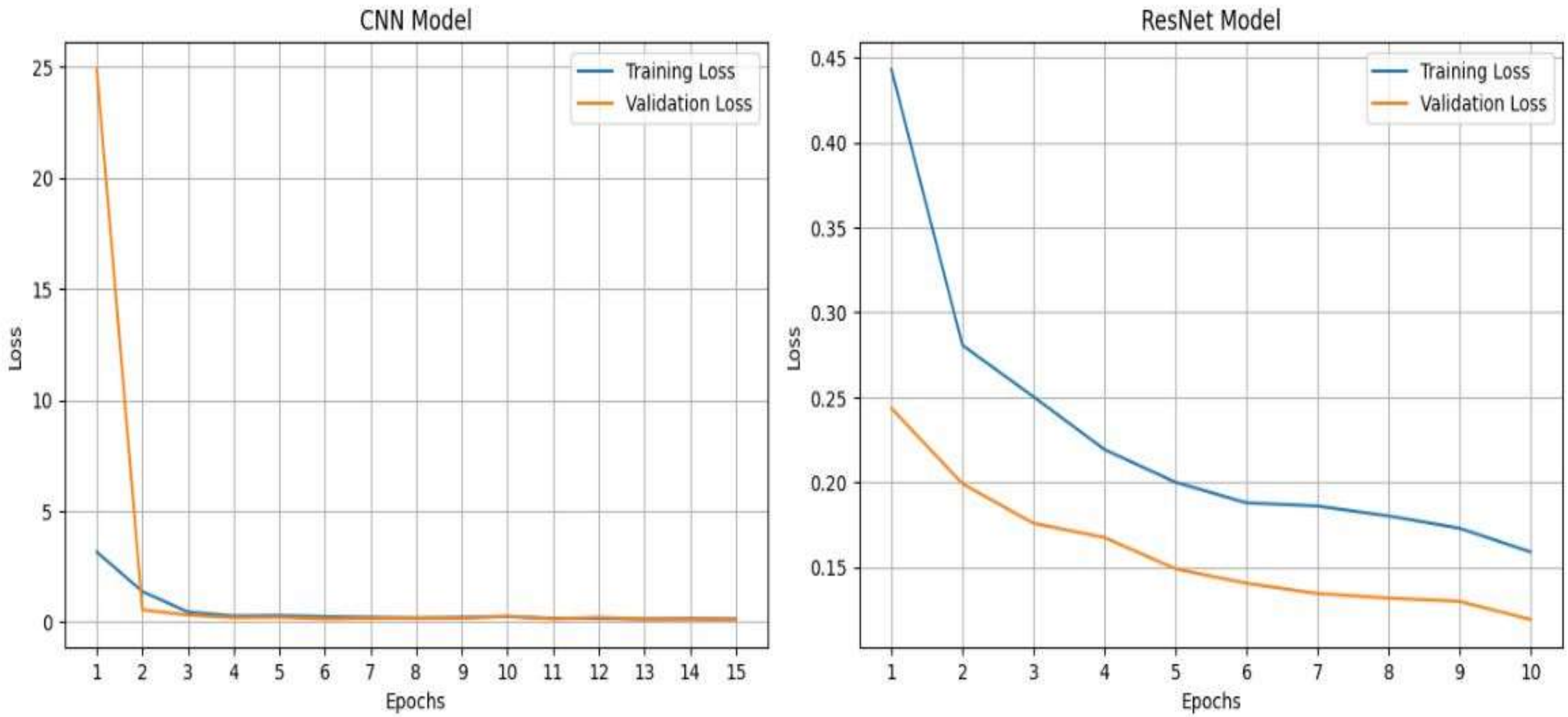

Fig. 04 - Training and Validation loss curve of CNN and Resnet50

Results and Analysis

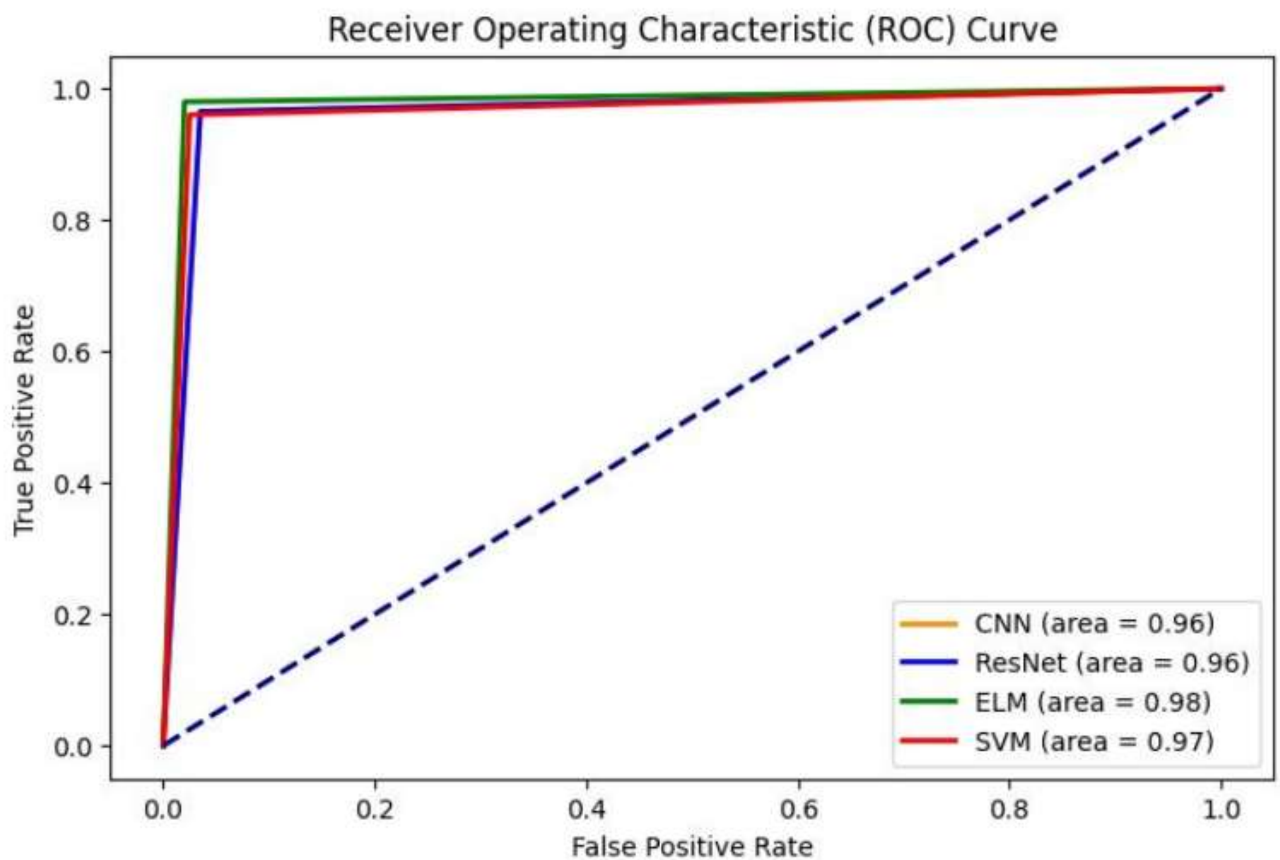

Fig. 05 – ROC curve comparison of the classifiers

Results and Analysis

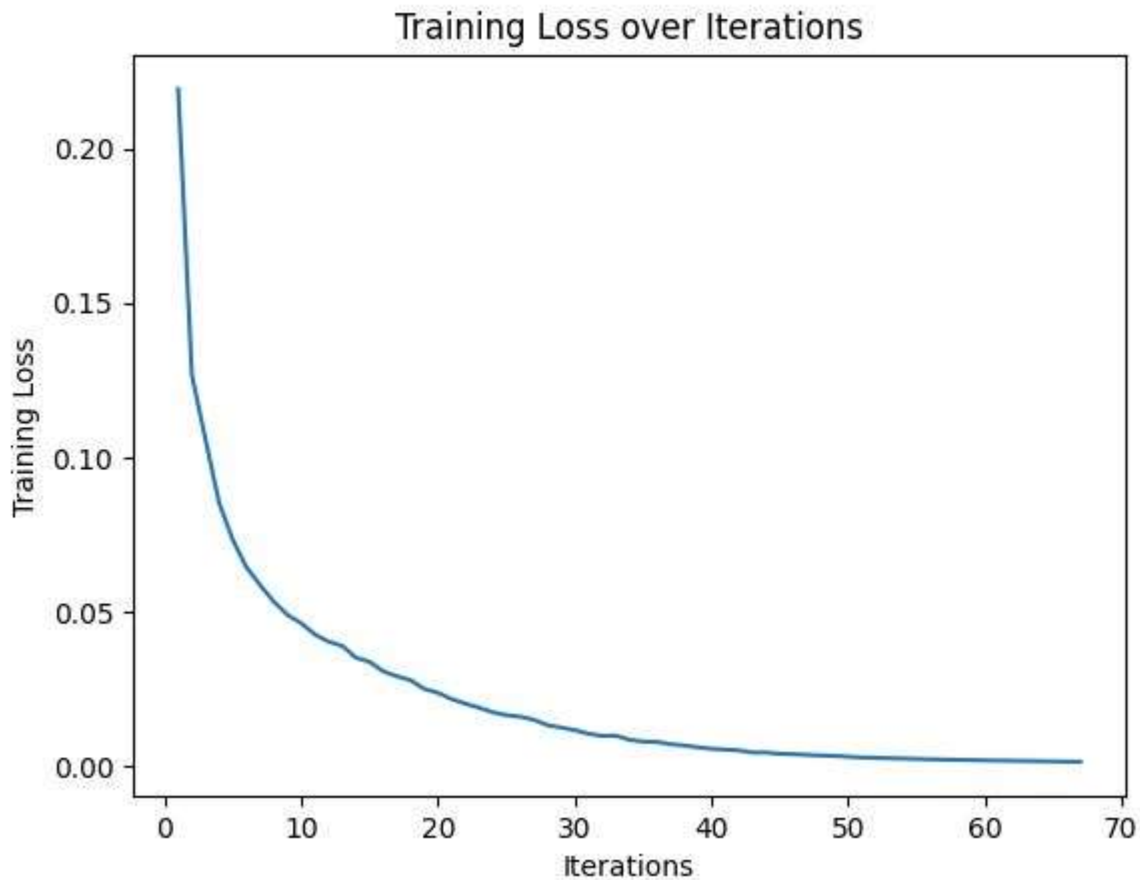

Fig. 06 - Training loss curve of the proposed ELM model

Results and Analysis

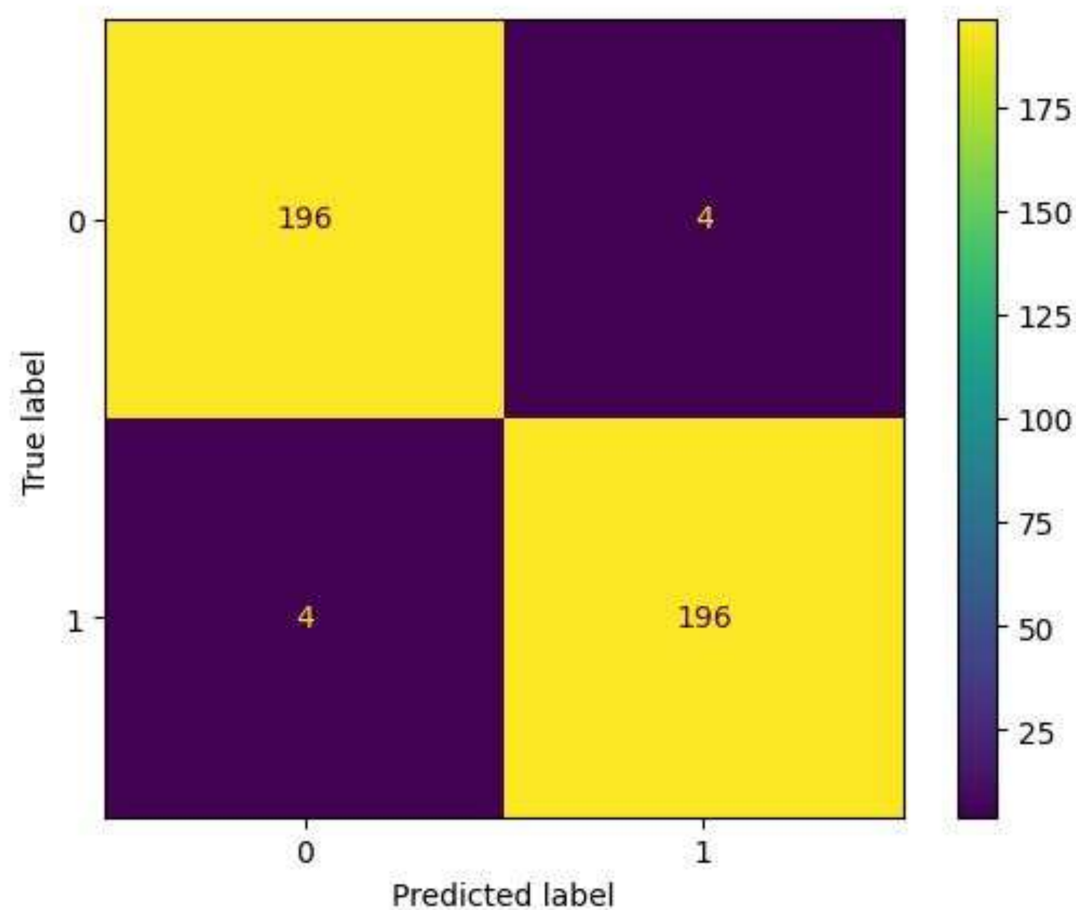

Fig. 07 - Confusion Matrix of the proposed ELM model

Results and Analysis

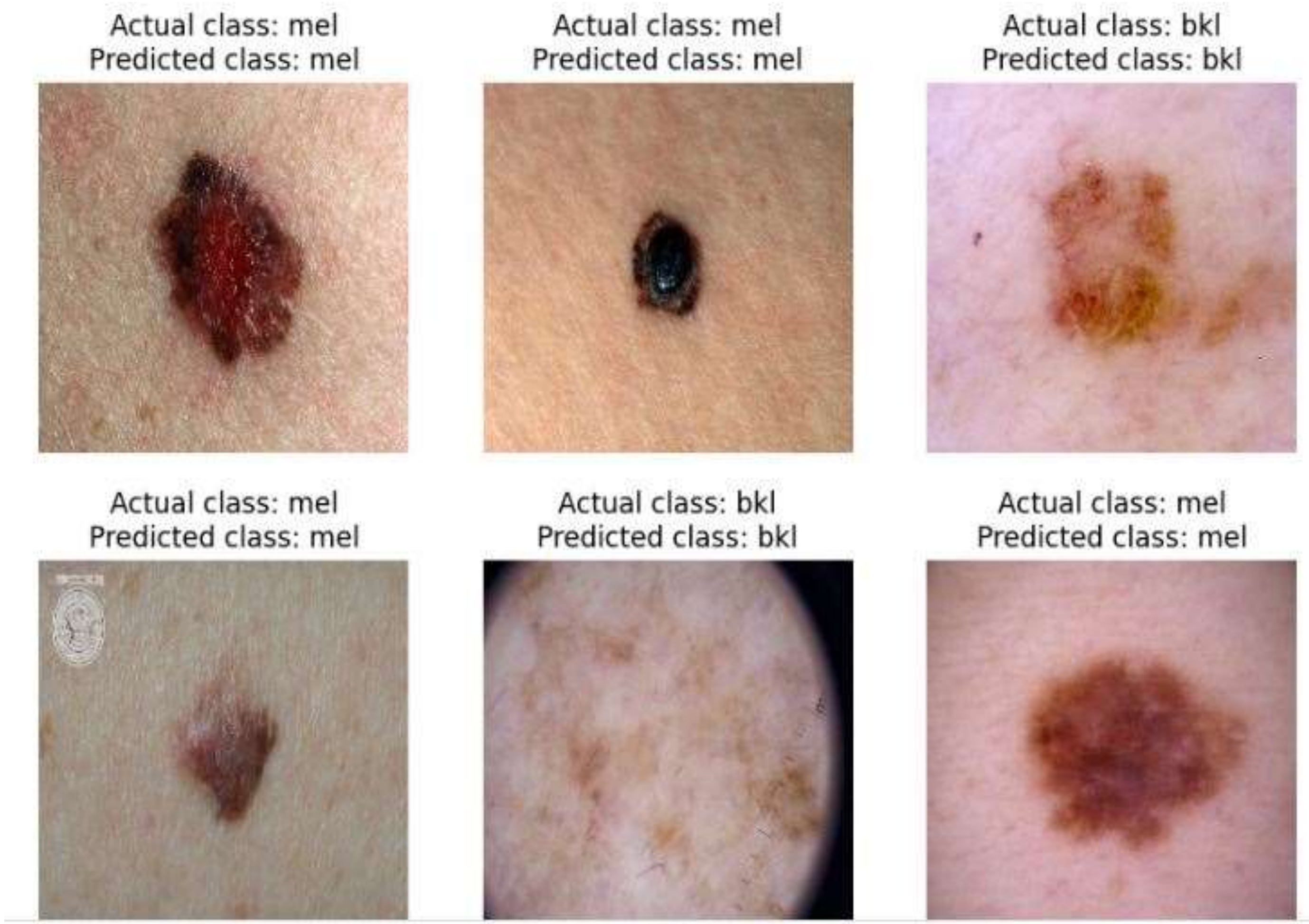

Fig. 08- Sample Predictions of the proposed ELM model

Conclusion & Future Work

- In our study we classifies Malignant and Benign skin lesions using deep learning and machine learning techniques like CNN, ResNet, SVM, and ELM.
- After Combining CNN and ResNet50 features with an ELM classifier(proposed model) we got an improved results across Precision, Accuracy, F1 score, and Recall of 98% in each case .
- In the future work we will focus on expanding the dataset and exploring moreover new machine learning and deep learning techniques to enhance the skin disease detection.

References

[1] Lei Bi, Jinman Kim, Euijoon Ahn, Dagan Feng, and Michael Fulham. Automatic melanoma detection via multi-scale lesion-biased representation and joint reverse classification. In 2016 IEEE 13th international symposium on biomedical imaging (ISBI), pages 1055–1058. IEEE, 2016.

[2] Noel Codella, Veronica Rotemberg, Philipp Tschandl, M. Emre Celebi, Stephen Dusza, David Gutman, Brian Helba, Aadi Kalloo, Konstantinos Liopyris, Michael Marchetti, Harald Kittler, and Allan Halpern. Skin lesion analysis toward melanoma detection 2018: A challenge hosted by the international skin imaging collaboration (ISIC). 2018.

[3] T. L. Diepgen, G. Yihune, and et al. Dermatology online atlas, n.d. Published online at: https://www.dermis.net/doia/.

[4] Debendra Muduli, Ratnakar Dash, and Banshidhar Majhi. Automated breast cancer detection in digital mammograms: A moth flame optimization based elm approach. Biomedical Signal Processing and Control, 59:101912, 2020.

[5] Gerald Schaefer, Bartosz Krawczyk, M Emre Celebi, and Hitoshi Iyatomi. An ensemble classification approach for melanoma diagnosis. Memetic Computing, 6:233–240, 2014.

[6] Santosh Kumar Sharma, Debendra Muduli, Rojalina Priyadarshini, Rakesh Ranjan Kumar, Abhinav Kumar, and Jitesh Pradhan. An evolutionary supply chain management service model based on deep learning features for automated glaucoma detection using fundus images. Engineering Applications of Artificial Intelligence, 128:107449, 2024.


Thank you!!!
...