Skin cancer detection

Under supervised of :
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Introduction

Skin cancer, driven by UV radiation, is a global concern. Melanoma, though only 1% of cases, causes 75% of deaths. Early detection is crucial, and manual diagnosis has limitations. Artificial intelligence, especially CNNs, improves diagnostic efficiency. Using the HAM10000 dataset, the study classifies skin cancer images, employing transfer learning for feature selection. The focus is on dataset balancing and model comparison, leading to the identification of the most effective model for lesion detection.

Dataset

The dataset used for this model is dataset gathered in 2018 by **The International Skin Imaging Collaboration (ISIC)**

consists of 10015 images → Consists of 7 classes → consist of the gender of each patient and age → The data also consist of the location of the cancer

Classes:
- Melanocytic nevi
- Benign keratosis-like lesions
- Dermatofibroma
- Actinic keratoses
- Vascular lesions
- Basal cell carcinoma
- Melanoma

Challenges

The data is unbalanced there is a majority in Melanocytic nevi cancer type, in this situation we can do 2 solution

data augmentation → limitation → In this case, we may lose some information from the image, and an expert in this disease must be consulted

Re-Sample the data by duplicate values → limitation → Resampling by duplicate images can increase accuracy and validation accuracy, and it is possible that this accuracy is incorrect.

Data visualization

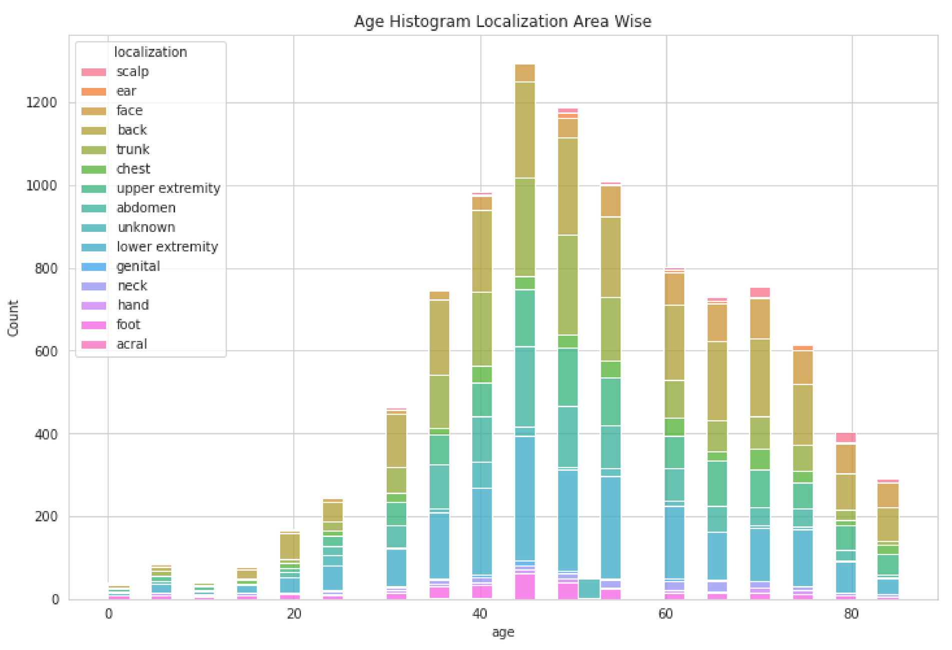


Fig.(1) age vs. location of cancer

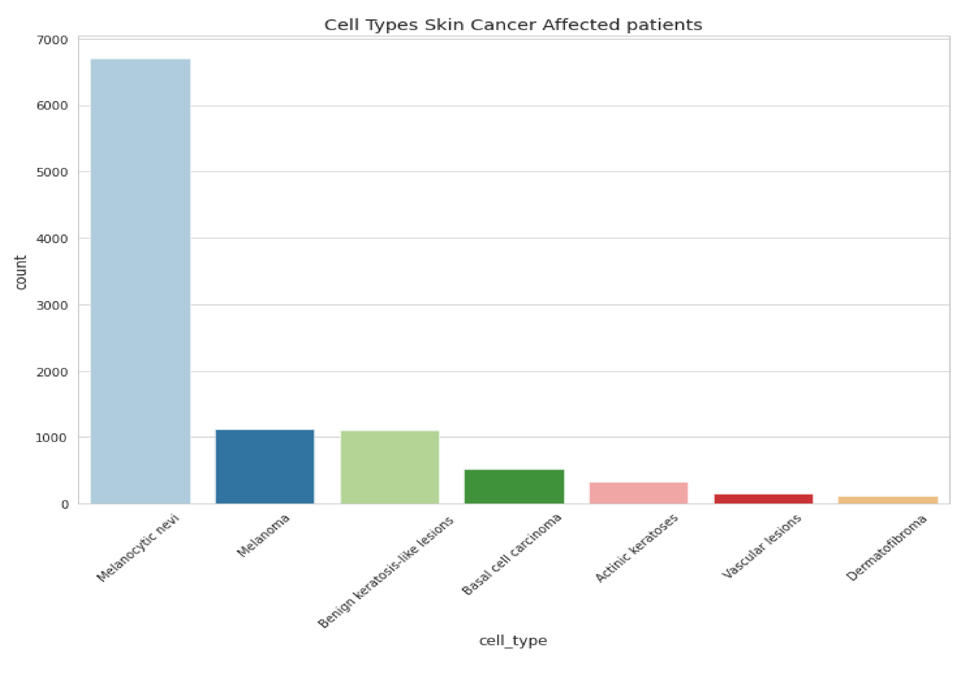


Fig.(2) the type of the skin cancer

Sample of the data

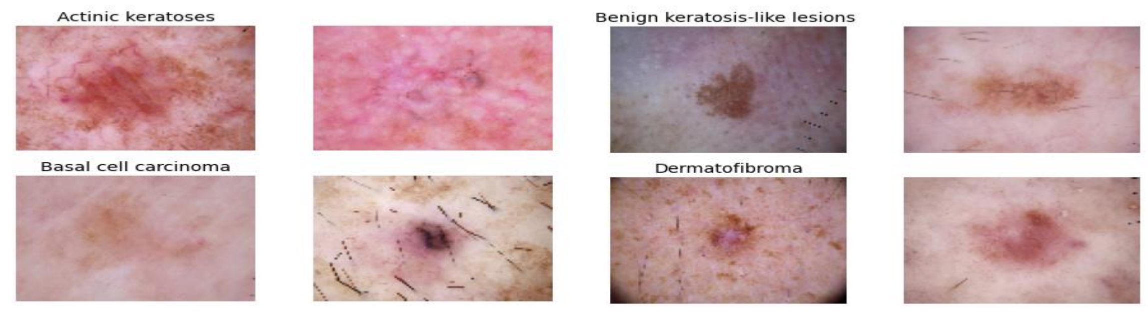


Fig.(3) show the actinic keratoses and basal cell carcinoma

Fig.(4) show the Benign keratosis-like lesions and dermatofibroma

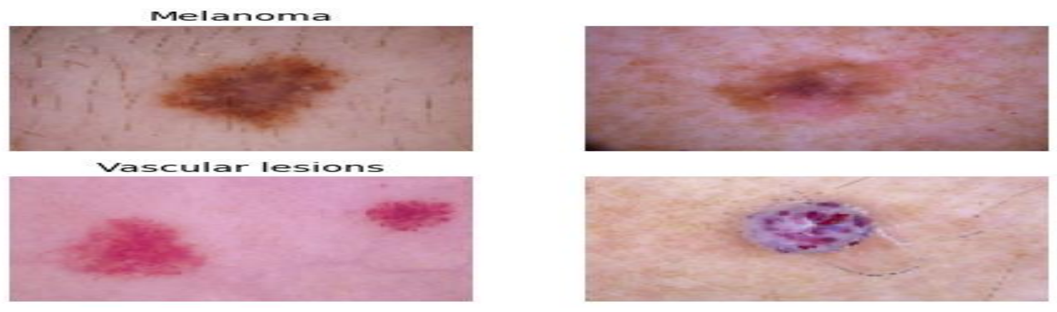


Fig.(5) show Melanoma and vascular lesions

Models

Our strategy is to apply many models with different activation function, loss function, sampling rate and data splitting, so we apply many models this is the table of some of it

	C-NN	Mobile NetV2	VGG16	Dense Net201
Accuracy	0.9157	0.9178	0.9472	0.8394
Val_accuracy	0.9078	0.9593	0.9441	0.7665

Adam Optimizer : This algorithm is used to accelerate the gradient descent algorithm by taking into consideration the ‘exponentially weighted average’ of the gradients. Using averages makes the algorithm converge towards the minima in a faster pace.

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)\left[\frac{\delta L}{\delta w_t}\right] \quad v_t = \beta_2 v_{t-1} + (1-\beta_2)\left[\frac{\delta L}{\delta w_t}\right]^2$$

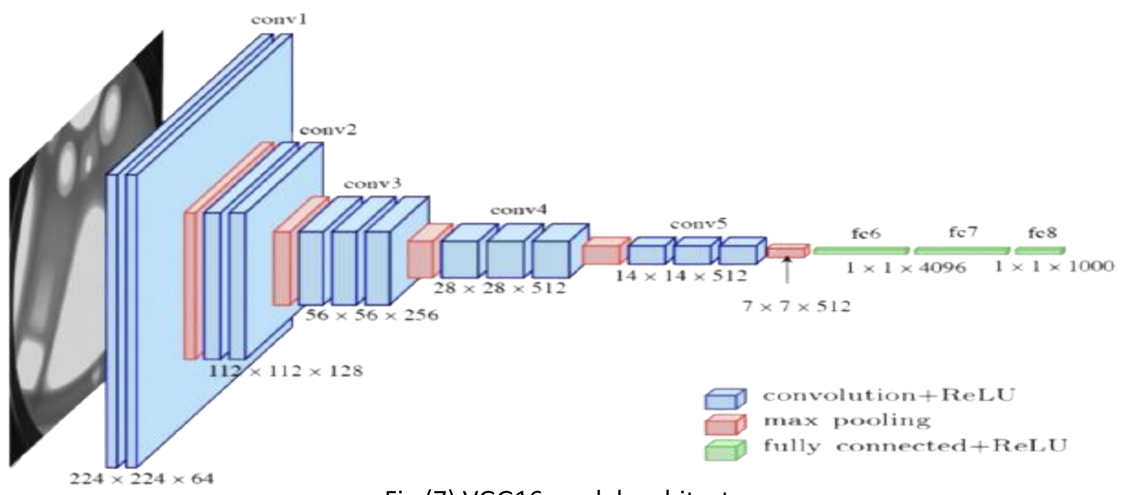


Fig.(7) VGG16 model architecture

Data augmentation

After researching more than one paper, we concluded that it is possible to do data augmentation, but without cutting, shifting, or shearing in the image

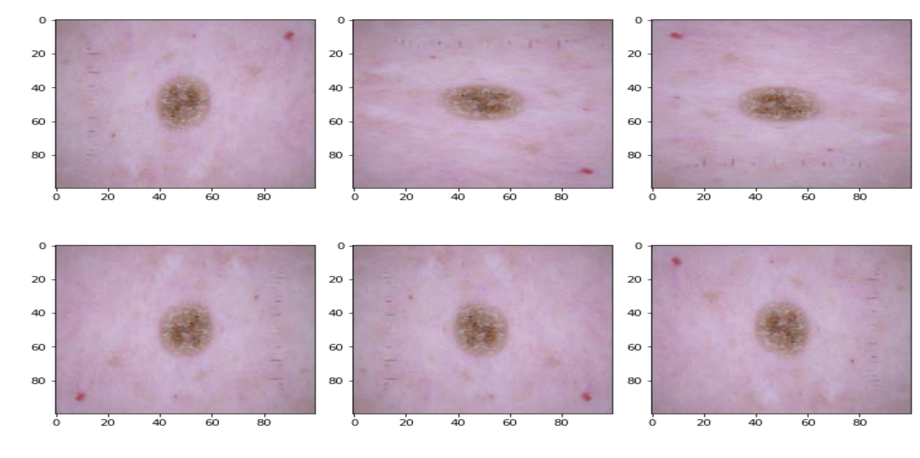


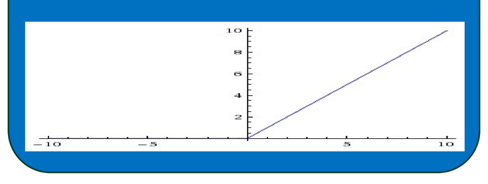
Fig.(6) Visualize the data augmented

VGG16 Model architecture

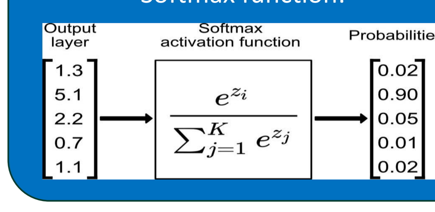
Epochs	Stages	Training / testing / validation	Batch size	Data augmentation	Data Re-sample
25	Two	80% 20% 10% of the training data	1000	True = { Rotation, flipping, zooming }	False (take the data un-balanced)

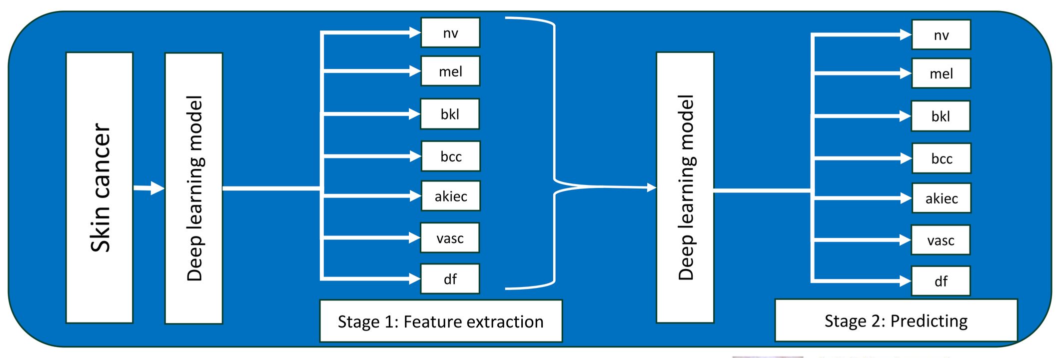
Activation functions

ReLu function: $f(x) = \begin{cases} x & \text{if } x > 0, \\ 0.01x & \text{otherwise.} \end{cases}$



Softmax function:





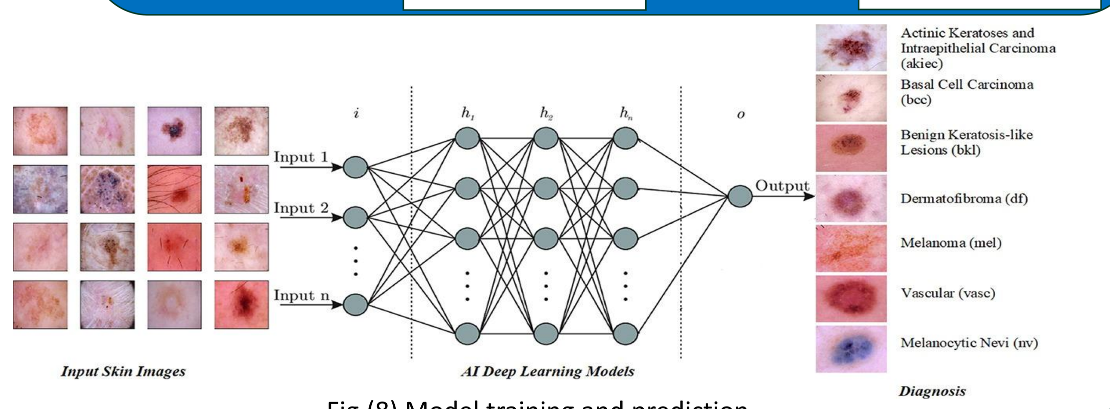


Fig.(8) Model training and prediction

Results of the best model

After the first model of VGG16 we set the full C-NN model as trainable and Fine-tune the full CNN + FC (fully connected layers)and train it again to get a better accuracy

Fig.(9) Model first stage accuracy, validation accuracy, loss and validation loss plotting

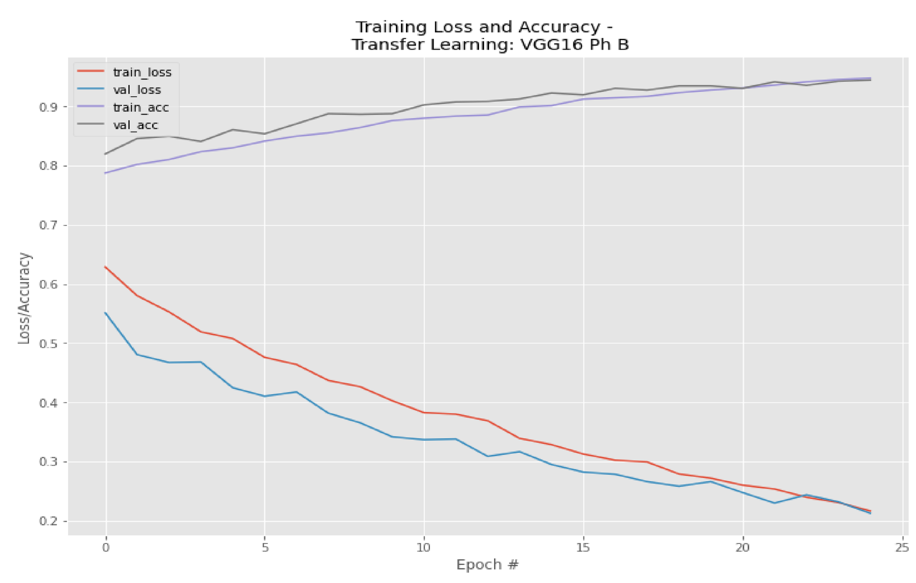


Fig.(10) Model second stage accuracy, validation accuracy, loss and validation loss plotting

Confusion matrix

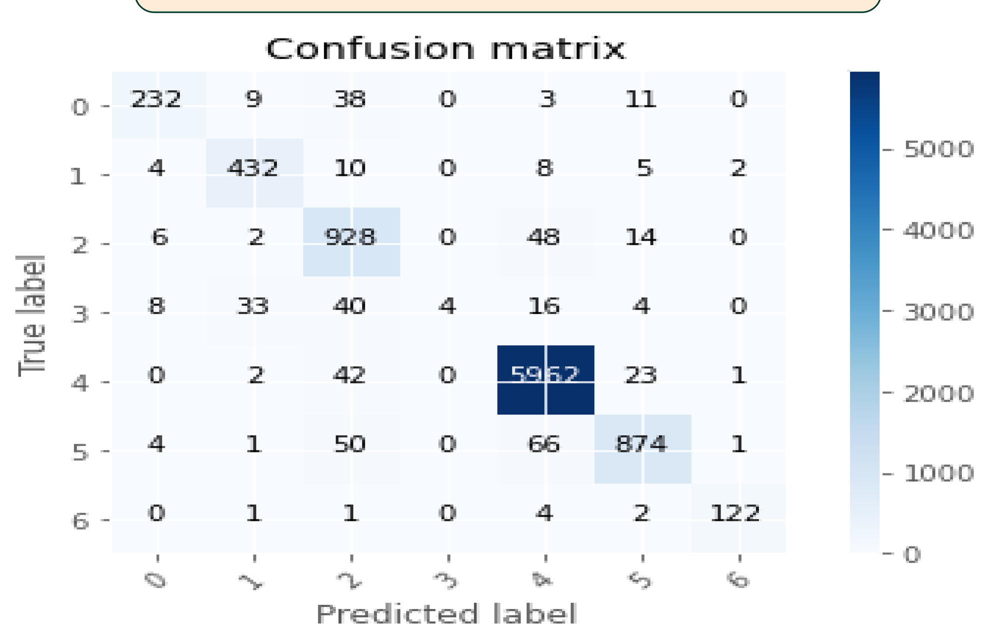


Fig.(11) Confusion matrix of VGG16 model to summarize the model performance

Samples of prediction

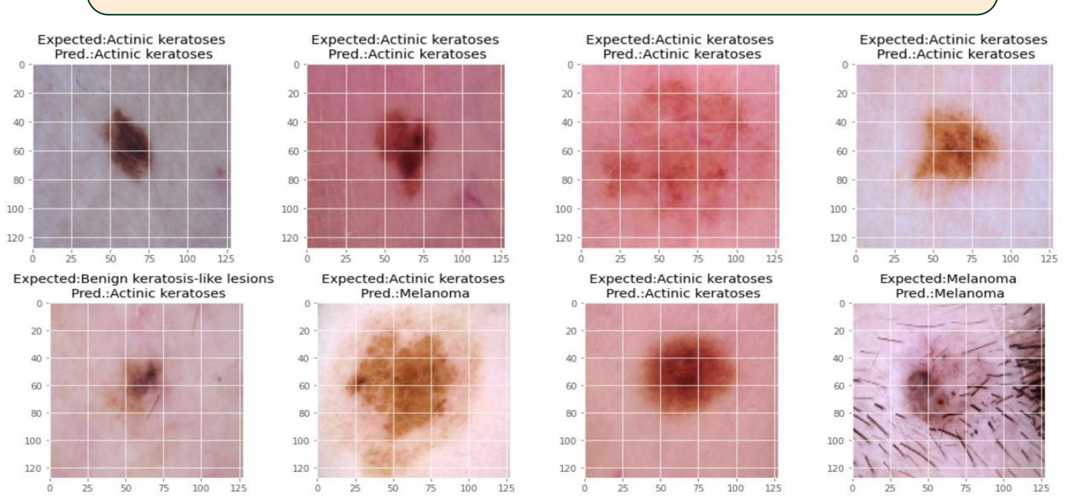


Fig.(12) Comparing between expected and predicted to evaluate the model

Conclusion

in our model we provided a transfer learning model by using CNN then several architectures as MobileNetV2, ,ResNet50, VGG16 and DenseNet201 that can be used to investigate any suspicious lesion. This method is applied to a dataset ham10000 of skin cancer disorders. We obtained adequate response in testing accuracy and training. In addition, the imbalances between the classes in our dataset hinders the model from acquiring better accuracy.

Future work

In the future, we will work on a dataset with better labeled skin lesions and images and contains less imbalances between its classes to acquire the best testing accuracy obtainable. As well as we will try using machine learning algorithms after transfer learning to view if it gets better results.

Team 1

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