Diagnosis of Skin Cancer Using Feature Engineering Techniques

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***Abstract*—Cancer is responsible for major mortality rate among human beings. Early diagnosis of Skin cancer especially Melanoma is having the potentiality to reduce morbidity as the major reason behind the disastrous repercussions of three out four homo-sapiens is due to skin cancer. Detection of cancer using machine learning and deep learning algorithms makes it very much feasible and economical. The ultimate focus of this paper is for detecting skin cancer at an early stage and helping to combat the increasing cases in skin cancer patients. In this paper, we have implemented different types of CNNs of different configurations on categorical classification where architectures were trained on different input image size and selection of best architecture was based on various metric evaluations like Maximum Accuracy, Precision, Recall, and F1 score and best architecture has achieved high accuracy and performed outstandingly in all the evaluation section. As per our study architecture 4 performed excellent in terms of every arena of metric evaluations. This architecture will be a helpful tool for diagnosing skin cancer at an early stage and will take the less computational cost for classifying the skin cancer disease.**

Keywords—Medical Imaging, Machine learning, Deep learning, Convolutional Neural Networks (CNNs), Skin Cancer

I. Introduction

Cancer, the madness of cells is still a nightmare to the people armed with sophisticated tools. Skin Cancer is an abnormal growth of cells in the epidermis. Over 5,000,000 newly diagnosed skin cancer cases are faced by doctors per year [1]. According to stats, over 350,000 cases with almost 60,000 deaths have occurred around the globe in the year 2015 [1]. In the past 5 years, Melanoma had increased drastically and the mortality rate has been highly increased due to the increase in spreading of this deadly skin cancer disease among homo-sapiens but early detection of Melanoma is much beneficial as 95% of peoples have successfully recovered after early diagnosis. Between the years 2002-2006 and 2007-2011, the average annual total cost for skin cancer has increased from $3.6 billion to $8.1 billion, and in terms of percentage, the growth was found to be 126.2% [2]. So early detection and proper treatment can help in successful recovery from skin cancer disease.

Machine Learning and Deep Learning have significantly contributed to a variety of fields of technology, the health sector, agricultural activities, and many more. Supervised and Unsupervised Machine Learning Models like Naïve bias, Support vector machines, Bi-directional LSTM, etc. are used for analyzing the Twitter sentiments and classifying them into positive and negative [3]. Similarly, for another sentiment analysis bi-directional LSTM and CNNs, gained high accuracy for understanding the public opinions for achieving the smarter techniques [4].

In the medical field, both of the modern techniques have given a smoother edge to the medical industries and technologies with their advanced algorithms of computer visions and neural networks. Critical diseases like pneumonia can be easily diagnosed by the implementation of CNN's on CXR images [5]. Micro-organisms detection is an important application of deep learning and machine learning [6]. Cell segmentation has been more accurately performed by using computer vision and deep learning techniques on cell images [7]. Graph neural networks can also be used for diagnosing critical diseases like cancer [8].

In this paper, we will analyze the performance metrics of all the different architectures of CNN's in terms of their computational costs by considering all three fields of validation accuracy, validation loss, and training time. The dataset was imbalanced so feature engineering and image augmentation played an important role in balancing the dataset for further process of training. We have implemented a of total 10 CNNs where 5 CNNs were trained on input image of size of 64x64 and rest 5 architectures were trained on input image of size 128x128. Finally the best architecture was selected based on the performance of architecture in all the metric evaluation section. The rest part of the paper is organized in the following way: II. Literature Review III. Dataset Preparation IV. Technology and Software Used V. Experimentations and Results VI. Conclusions and Future works. We will consider the ideal architecture for finding and diagnosing skin cancer which is low in computation cost.

II. Literature Review

Nowadays as every field is getting a major contribution from deep learning, machine learning, and big data. Medical sciences are a majorly contributed field from these areas. Cancer is a dangerous disease and skin cancer is one of the deadliest cancer which is getting a major contribution from these niche areas like machine learning and deep learning. As most of the research papers are more focused on deep learning so Esteva *et al.* (2017) have classified skin cancers from a dermatologist level with the help of deep learning by implementing CNN-PA and gained the highest three-way accuracy of 72.1% and for nine-way accuracy of 55.4% [9]. H. Nahata, *et al.* (2020) also have come up with different deep learning solutions for the diagnosis of skin cancer and transfer learning was used for classifying lesions of skin cancers and best performer was found to be InceptionResnet with the average accuracy of 91% but there was no-self configured models for classification and implementation [10]. A. Dascalu, *et al.* (2019) did a sound analysis algorithm and deep learning for skin cancer detection and had SMP analysis metrics had an AUC-ROC of 0.814 and results were in terms of F2-Score, Sensitivity, and Specificity and positive predictive value [11]. X. Dai, *et al.* (2019) has come with solutions for deploying the deep learning skin cancer detection model on mobile devices, where all the computations and the inferences are computed locally such that it can reduce latency, saves bandwidth, and improves privacy [12]. K. Hosny, *et al.* (2018) has applied transfer learning techniques applied to the AlexNet and achieved an accuracy of 0.9861, classifying three lesions [13]. A. Khamparia, *et al.* (2020) applied different transfer learning models like VGG19, Inception V3, ResNet50, and SqueezeNet to train on the skin cancer images for classifying the cancers lesions [14]. F. Pollastri, *et al.* (2020) has applied Generative Adversarial Neural Networks (GANs) for making the data augmentation process straightforward where the model generates both images as well as their segmentation masks, to analyze the impact of the efficacy of the architecture on the quality and the diversity of the synthetic images [15].

There are many problems in the medical fields but technologies like deep learning and machine learning are contributing and providing better solutions for diagnosis and classification. With the help of several cutting-edge medical tools and also with the help of a machine and deep learning, it has been easier to unfold the truths. Not only specific to skin lesions, in other areas too deep learning has been impactful in many cases. F. Dong, *et al.* (2017) approached automated malaria detection using deep convolutional neural networks [16]. S. Das *et al.* (2020) made a comparative study for heart disease detection using core machine learning and deep learning techniques [17]. Poplin *et al.* detected the risk factors in heart disease and J. Rubin *et al.* detected abnormal heart disease using deep learning respectively [18-19]. ECG graphs are been classified using deep CNN models and they have gained good accuracy [20]. A. Hauptmann *et al.* (2019) approached the real-time cardiovascular MR with Spatio-temporal artifact suppression using deep learning [21]. Though in the paradigm of generative modeling, Unsupervised Boltzmann Machines (UBMs) are very much significant for the extraction of features, neuroimaging, recommender systems, etc. [22].

With the help of data augmentations and CNNs, J. Salamon, *et al.* (2017) classified different types of environmental sound data with good accuracy [23]. Generative models are also one of the most important aspects of deep learning, several contributions in generative models are also being done like a comprehensive survey for the analysis of the generative models in machine learning [24]. R. Salakhutdinov, build intelligent systems with deep generative models from high dimensional sensory data to solve several AI-related problems [25]. It has been seen that credit card fraud detection can be handled robustly using proper deep learning models and data mining techniques [26].

Frid-Adaret *et al.* made an approach towards synthetic medical image data augmentations with the help of GANs which boosted the technique of data augmentation [27]. C. Han, *et al.* developed combined noise to image and image to image GANs for augmentations and brain tumor classifications [28]. Not only CNNs, nowadays Deep Reinforcement Learning is used for image classifications. A. Hafiz, *et al.* developed a state of the model with two state Q-learning for image classification [29]. Although many implementations were on skin cancer there are several limitations like we can see that most of the papers were directed towards transfer learning techniques where they have used pre-trained models on various datasets and there was the repetition of datasets where a single dataset was used by many authors and few of them were performed on small scale and no different conditions were implemented so that we can check the stability of architectures. So many radiologists faced issues for the classification of skin cancer lesions into different categories.

III. DATA PREPARATION

This section will brief all the information regarding the dataset used and dataset preparation. This section comprises 2 sub-parts *A. Dataset Used B. Dataset Preparation.*

A. Dataset Used

The dataset was retrieved from the International Skin Imaging Collaboration (ISIC) [1]. Since 2015, ISIC is organizing these international challenges for skin lesions for melanoma analysis. For implementation on large scale operation of merging was performed on the dataset which was published during 2018 and 2019 by ISIC.

The dataset can be categorized into 7 classes and Table I shows all the categories of skin cancer present in the dataset and Fig. 1 shows the information of images in the dataset along with the class names in detail before data preparation. Before data preparation and data augmentation, our dataset was imbalanced in various classes where Melanocytic Nevus was having a large number of 6660 total images and Dermatofibroma had the least number of 115 images.

TABLE I. DISTRIBUTION OF RAW DATA

Class names	Number of images
Melanoma	1111
Melanocytic Nevus	6660
Basal Cell Carcinoma	514
Actinic Keratosis	327
Benign Keratosis	1089
Dermatofibroma	115
Vascular Lesion	142

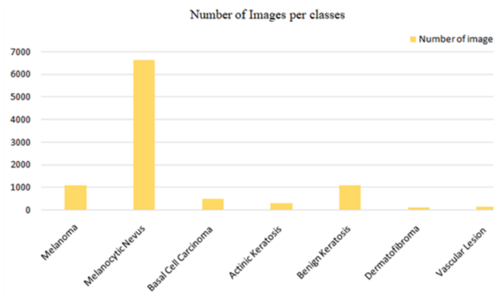

Fig. 1. The distribution of the raw dataset

B. Dataset Preparation

For balancing the highly imbalanced dataset, feature engineering and data augmentation played a crucial role in dataset preparation. Image augmentation works on different parameters like shear, zoom, rescale, flipping, whitening, transforms random rotations and shifts. In our approach, we rotate, shear, brightness increment, width, and height shifting in the training images for increasing the minority classes and balancing the dataset where augmentation was performed by using Keras Image Data Generator. The instance of Actinic Keratosis augmented images has been shown in Fig. 2 and Table II shows the distribution of balanced dataset for training and testing.

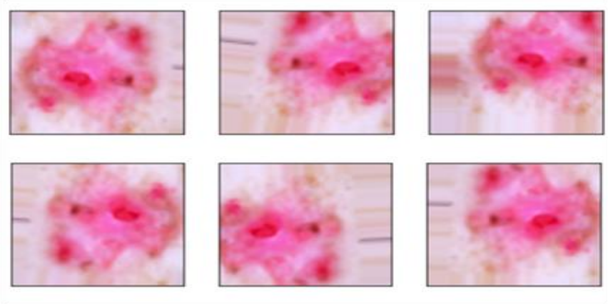

Fig. 2. Augmented images of a single image of class Actinic Keratosis

TABLE II. DISTRIBUTION OF THE FEATURE ENGINEERED DATA

	Melanocytic nevus	Melanoma	Actinic Keratosis	Benign Keratosis like lesions	Dermato fibroma	Vascular lesions	Basal cell carcinoma
Training	5374	5539	5215	5213	4991	4969	4919
Testing	1286	1327	1325	1321	1219	1279	1249
Total	6660	6666	6540	6534	6210	6248	6168

IV. TECHNOLOGY AND SOFTWARE USED

A. Convolutional Neural Networks

Convolutional Neural Networks play a vital role in the field of computer vision and deep learning techniques. CNN acts as a backbone in Deep learning and has many applications for dealing with day-to-day problems like detection of Malaria [30], or tasks like handwriting recognition [31], ECG heartbeats classifications [32], and COVID-19 detection [33]. Convolutional layers can easily overcome the problem of translation variance. Convolutional Layers work on the principle of the Convolutional theorem, and they also undergo the same process as feed-forward propagation and backward propagation. Features are extracted from different classes so that they can classify different images based on their extracted features and spatial relationship between them.

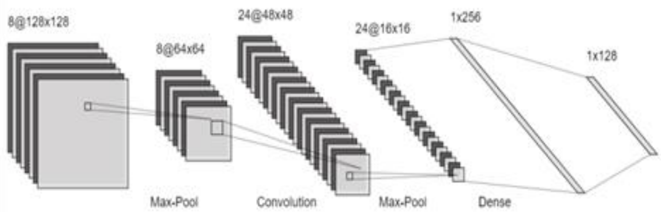

Fig. 3. A fully convolutional neural network

CNN's are composed of 4 main types of layers – Convolutional, Max-Pooling, Flattening, and Full-Connection. Convolution has the property of translation in-variance which can be defined as

$$x\big(y(n)\big) = y(x(n)) \qquad (1)$$

Property of the original function can be easily characterized and manipulated in the new function. Images will be considered as a discrete object then convolutional can be expressed as

$$(f * g)[n] = \sum_{m=-M}^{m=+M} f[n-m]g[m] \qquad (2)$$

Where f is the input image and g is the kernel function such that g is being convoluted over f and then passed into an activation function named as Rectified Linear Unit, for getting output as features.

B. Software and Hardware Used

Various CNN architectures trained for this machine learning analysis Python 3 with the Keras and TensorFlow were used with a jupyter notebook. The hardware workstation is Intel i7 10^{th} generation and 16 GB RAM.

V. EXPERIMENTATION AND RESULTS

This section focuses on the implementation and performance of various CNN architectures. For the different implementations, we had various parameters such as the number of Convolutional layers and Artificial layers, Batch Normalization, Dropout, and feature detection. Implementation majorly focuses on two types of Input Image Sizes 64x64 and 128x128. So from each of the image sizes, we select the best model after comparing their metrics section in terms of Precision, Recall, F1-Score, and Accuracy. This section is being divided into 2 subsections as *A.* Experiment and Analysis, *B.* Results of selected architecture.

A. Experiment and Analysis

Construction of all the architectures was based on Input Image Sizes, Regularization conditions like BN and DO. Image input sizes were 64x64 and 128x128. Various Abbreviations are used in this section and Table IV is given in Table III. Several different parameters like the number of the CL, the number of the AL (dense layers), and regularization parameters like BN and DO have been applied to achieve precise and accurate results.

TABLE III. ABBREVIATIONS USED

Notation	Meaning of the Notation
CL	Convolutional Layer
FL	Flatten

AL	Artificial Layer
BN	Batch Normalization
DO	Dropout
PS	Pooling Size (Assumed to be square matrix)
KS	Kernel Size (layer-wise)
IS	Input Size
LVCEL	Least Validation Cross Entropy Loss
MVA	Maximum Validation Accuracy
TT	Time Taken (in seconds)
FD	Feature Detected

The best architecture was selected based on Accuracy, Precision, Recall, F1-score, and Confusion Matrix from the two different image input sizes. Table IV contains all the information regarding the CNN architectures for (64, 64) image, and (128, 128) image size, with the maximum validation accuracy, the least validation loss, and the time taken. Among them, Architecture 2 is the best architecture for the (64, 64) and Architecture 4 for the (128, 128) images. As the complexity of the architectures i.e. as the number of the parameters has increased the computational time has increased for all the architectures of (64, 64) images and (128,128) images respectively. So complexity is directly proportional to computational time.

From Architecture 2 of 64x64, we can observe it took only 395 seconds for training which is lowest and better when compared to all the architectures present for training. On the other hand, the time taken by the architectures to train the (128,128) images was comparatively higher than the (64, 64) images training time, and according to an observation we can say that image size is directly proportional to training time

From Table IV, we can observe that Architecture 2 of 64x64 performed excellent in terms of MVA and gained the value of 0.9768 and had LVCEL of 0.0968 and TT was 2490 seconds. On the other hand, Architecture 4 of 128x128 performed very well in all the sections where MVA was found to be 0.9834 and LVCEL was found to be 0.0610, and training time was 9468 seconds. Architecture 3 of 64x64 images gained the lowest accuracy when compared to other architectures and in 128x128 Architecture 2 was the lowest accuracy scorer. So for further sections, we have selected Architecture 2 of 64x64 and Architecture 4 of 128x128 for the metric evaluation section. We can observe from below Table IV that our architectures have performed outstandingly in all the fields of LVCEL, MVA, and TT when compared to other competitor architectures.

TABLE IV. PERFORMANCE OF ALL ARCHITECTURES

Model Architecture No:	CL	AL	Regularization		IS	FD	KS	PS	LVCEL	MVA	TT
			BN	DO							
Performances of the CNN architectures for (64,64) images											
1	2	2	✕	✕	(64,64,3)	{16,32}	(3,3)	(2,2)	0.1853	0.9481	395
2	**4**	**4**	✕	✕	**(64,64,3)**	**{16,16,32,64}**	**(3,3)**	**(2,2)**	**0.0968**	**0.9768**	**2490**
3	4	3	✕	✓	(64,64,3)	{32,64,64,64}	(3,3)	(2,2)	0.2244	0.9230	2375
4	4	2	✕	✓	(64,64,3)	{32,32,64,128}	(3,3)	(2,2)	0.1103	0.9638	1234
5	5	4	✓	✓	(64,64,3)	{32,64,64,128,128}	(3,3)	(2,2)	0.1392	0.9529	5436
Performances of the CNN architectures for (128,128) images											
1	2	3	✕	✕	(128,128,3)	{16,32}	(3,3)	(2,2)	0.1371	0.9649	1963
2	6	4	✕	✕	(128,128,3)	{16,32,32,64,64,6}	(3,3)	(2,2)	0.2468	0.9487	6758
3	3	4	✕	✓	(128,128,3)	{32,32,64}	(3,3)	(2,2)	0.1082	0.9656	7283
4	**4**	**3**	✕	✓	**(128,128,3)**	**{32,64,128}**	**(3,3)**	**(2,2)**	**0.0610**	**0.9834**	**9468**
5	4	5	✓	✓	(128,128,3)	{32,64,128,128}	(3,3)	(2,2)	0.0777	0.9734	16058

Fig.4, Fig. 5, and Fig. 6 show the MVA, LVCEL, and TT of all the architectures of 64x64 and 128x128 image sizes and by comparing all the architectures we have selected the best architecture in both the input sizes of images and we have compared them in next section. Table V shows all the metric evaluations of all the architectures and we can observe our selected architectures have performed outstandingly in all the domains so in the next section we will compare our best-selected architectures.

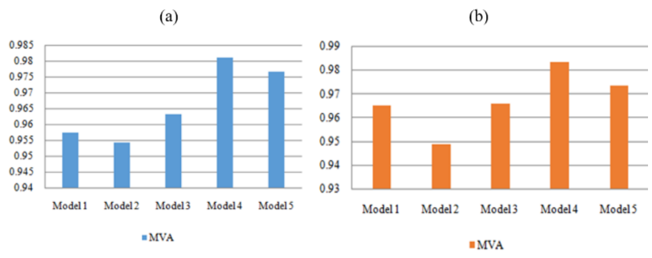

Fig. 4. (a) MVA for (64,64) (b) MVA for (128,128)

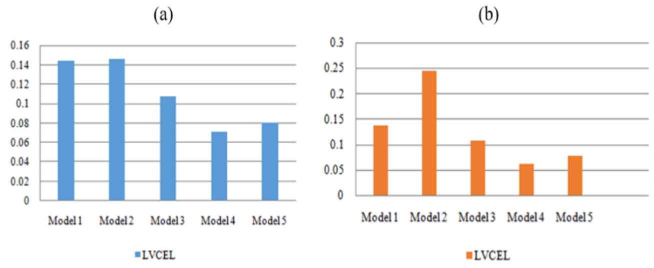

Fig. 5. (a) LVCEL for (64, 64) (b) LVCEL for (128,128)

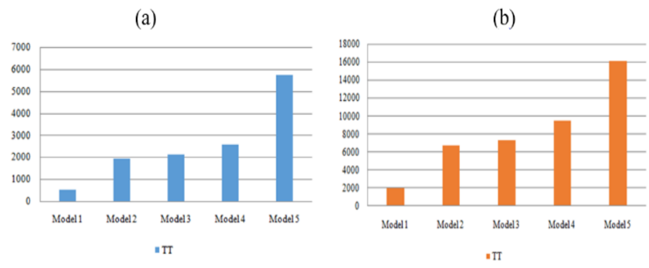

Fig. 6. (a) TT for (64,64) (b) TT for (128,128)

TABLE V. PERFORMANCE METRICS OF ALL THE ARCHITECTURES

Architecture No:	Accuracy	Precision	Recall	F1-score
Metric comparisons of the architectures for the (64, 64) images				
1	0.9481	0.9457	0.9457	0.9457
2	0.9768	0.9700	0.9671	0.9685
3	0.9230	0.9300	0.9214	0.9256
4	0.9638	0.9614	0.9585	0.9599
5	0.9529	0.9557	0.9514	0.9535
Metric comparisons of the architectures for the (128, 128) images				
1	0.9649	0.9034	0.9123	0.9078
2	0.9487	0.9320	0.9120	0.9219
3	0.9656	0.9400	0.9465	0.9432
4	0.9834	0.9784	0.9634	0.9708
5	0.9734	0.9745	0.9772	0.9759

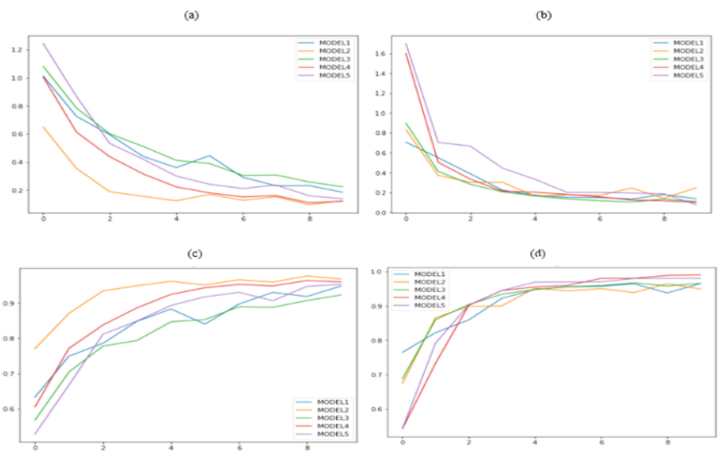

Fig. 7. (a) The validation loss of the architectures during training for (64, 64) images (b) The validation loss of the architectures during training for (128, 128) images. (c) The validation accuracy of the architectures during training for (64, 64) images (d) The validation accuracy of the architectures during training for (128, 128) image

B. *Results of the Selected Architectures*

From all the architectures, we have selected Architecture 2 and 4 as the best Architecture for 64x64 images and 128x128 images respectively. In this section, we will be seeing the evaluation metrics of both the architecture and will find the best among them. The evaluation metrics were calculated from the confusion matrix are the Precision, Recall, and F1 scores respectively. Mathematically, the metrics Precision, Recall, and F1-scores are defined in Equations 3, 4, and 5 respectively.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{3}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{4}$$

$$\text{F1 Score} = \frac{(2 * \text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})} \tag{5}$$

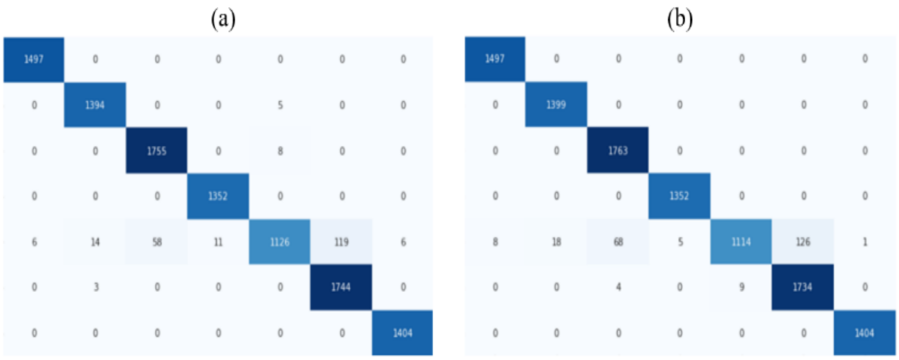

Fig. 8. (a) Confusion Matrix of Architecture 2 of (64, 64) (b) Confusion Matrix of Architecture 4 of (128, 128)

TABLE VI. CONFIGURATION OF SELECTED ARCHITECTURES

Configuration of Selected Architectures											
Model Architecture No:	**CL**	**AL**	**Regularization**		**IS**	**FD**	**KS**	**PS**	**LVCEL**	**MVA**	**TT**
			BN	**DO**							
2	4	4	✕	✕	(64,64,3)	{16,16,32,64}	(3,3)	(2,2)	0.0968	0.9768	**2490**
4	4	3	✕	✓	(128,128,3)	{32,64,128}	(3,3)	(2,2)	**0.0610**	**0.9834**	9468

TABLE VII. COMPARISON OF SELECTED ARCHITECTURES

Metric Evaluation of Selected Architectures					
Model No.	**Input Image Size**	**Accuracy**	**Precision**	**Recall**	**F1-score**
2	(64,64)	0.9768	0.9700	**0.9671**	0.9685
4	(128,128)	**0.9834**	**0.9784**	0.9634	**0.9708**

From confusion matrices and Table VI and VII, we can conclude that Architecture 4 of (128, 128) performed much better than Architecture 2 of (64, 64) in terms of all the metric evaluations performed. From Table VI and Table VII, we can observe that Architecture 4 of 128x128 Input Image Size performed outstandingly and gained high accuracy and stability when we compare with our Architecture 2 of 64x64. Architecture 4 performed better in the fields of MVA, LVCEL, Precision, Recall, and F1-Score. So we can state that Architecture 4 of 128x 128 was the best and ideal architecture for diagnosing skin cancer disease.

VI. CONCLUSION AND FUTURE WORKS

This paper makes an effort to find the optimal architecture for the most stable performance the diagnosis of skin cancer. Based on different parameters like Precision, Recall, F1-score, and confusion matrix, it is found that Architecture 4 is the most optimal structure for the (128, 128) images. Our proposed architecture gain an accuracy of 0.9834. Though the main caveats of the total experimentations was that, it may not be generalized for a very big amount of data, having a lot of variation. We admit architecture 4 performed best and can gain more stability and accuracy if we do small adjustments and experimented upon more.

Future works of classification of these cancer images can be done more efficiently and more accurately with the help of GANs. Using GANs, we can generate more data rather than using data augmentation techniques. This would also lead us to make a more generalized model and maintaining that descent accuracy at the same time. Also at the same time, we can work out the works of deep fakes simultaneously. Those generated images will also help to detect the fake and real images by detecting the anomalies which can be used in forensic sciences too and thus achieving multiple goals with the same models. Transfer learning can also be beneficial for getting more accurate results for classifying skin cancer disease.

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