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Skin Cancer Detection Using Deep Learning Algorithms

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Abstract: Skin disorders are very difficult to diagnose since many conditions have similar appearances, which makes it hard to tell them apart. While melanoma remains the most prevalent form of skin cancer, other illnesses are now known to be fatal. The most significant barrier to the development of automated dermatological systems is the scarcity of thorough and thorough data.This thesis introduces a robust deep learning architecture tailored for skin cancer diagnosis through the use of transfer learning on two types of convolutional neural networks (CNNs). These consist of a basic classifier and a two-tiered hierarchical classifier that makes use of two advanced CNNs. Differentiating between seven categories of nevi is the goal because precise diagnosis and treatment planning depend on it. The study's primary dataset is the HAM10000 dataset, a sizable collection of dermoscopic photos. Model performance is improved through the process of integrating multiple data sources. The outcomes unequivocally show how successful the DenseNet201 network is in this situation. This special combination reduces false positives while improving classification and Fmeasure accuracy. The test revealed that, surprisingly, the simple model performed better than the hierarchical two level model. The hierarchical approach is more straightforward than that, despite its attempt to provide classification at various levels. Specifically, the most successful level of binary classification is the first one, especially when it comes to differentiating lesions with and without nevus. This paper emphasizes the significance of applying deep learning methods particularly transfer learning to address the challenging skin cancer categorization issue. It is stressed how crucial data sets like HAM10000 are to the development of dermatological research. The outcomes validate the effectiveness of DenseNet201 in categorizing skin conditions and emphasize the necessity of refining the classification algorithm to produce more dependable, precise, and enhanced diagnoses, hence enhancing dermatological care.

Keywords: Deep learning; image; melanoma; skin cancer; classification.

1. Introduction

With a staggering 75% fatality rate and a frightening 14% spike in melanoma occurrences, skin cancer is a severe threat to public health according to the American Tumor Council claims. It is still hope because early discovery of cancer can significantly increase survival rates, despite these depressing statics. Early diagnosis and treatment are crucial in providing patients with a positive prognosis. Early intervention not only increases the likelihood of a positive result, but it also makes less intrusive treatment choices available. Individual chances of survival are greatly increased by putting an emphasis on early detection and treatment, especially for those with melanoma. This emphasizes how crucial it is to continue the fight against this potentially fatal illness by promoting preventative healthcare practices, frequent screenings, and public awareness campaigns.[1].

To fully understand the nuances of skin cancer, physicians must have a profound understanding of the intricacies of the skin. The three primary layers of skin are the dermis, epidermis, and subcutaneous fat. Unchecked aberrant cell development within these layers leads to the development of skin cancer. New cells constantly replace old ones in the skin as they age naturally. This process is known as skin renewal. However, when this renewal process goes wrong, old cells do not die and instead continue to exist, which leads to the production of new cells in the wrong locations. An excess of skin cells causes a tissue mass to grow, which in turn develops into a tumor. With this fundamental knowledge, healthcare providers may identify and treat skin cancer more effectively, emphasizing of prompt identification and intervention in attaining the best possible outcomes for patients.[2].

The first and most common method used by dermatologists to determine the type of skin lesion is visual inspection. Assessing diverse lesion aspects is necessary for the distinction between benign and malignant entities. Important factors in this visual assessment are distribution, size, shape, border, symmetry, and color. However, because color-based diagnoses rely on subjective assessments of light and how it interacts with the skin, they contribute arbitrariness. The subjective nature of color assessment complicates the diagnosing process, prompting a constant search for more objective and accurate techniques. The goal of ongoing technological advancements in imaging and other diagnostic techniques is to supplement visual assessments and give dermatologists a more complete and precise way to identify and categorize skin lesions as soon as possible.[4].

Since melanocytes, which are the cells that give skin its color, are the primary cause of melanoma, early identification is essential to a good prognosis. The length of time since melanoma was discovered has a substantial influence on treatment results. If left untreated, melanoma has the ability to spread to other body parts and cause permanent harm. The challenge stems from the fact that benign nevi and melanomas share characteristics that make early detection more challenging. It is difficult for dermatologists to distinguish between benign and malignant moles, a problem that is exacerbated by the absence of a trustworthy classification system. In order to improve the capacity to differentiate benign from malignant skin lesions, better early interventions, and better patient outcomes are ultimately dependent on improved diagnostic tools and standardized standards [5].

Concerning trends include recreational sunbathing and a history of sunburn being linked to the rise in melanoma incidence worldwide. Because DNA genes control the processes of cell division and reproduction in every cell in the body, melanoma develops similarly to other malignancies. There are other genes that are inconsequentially similar to those responsible for melanoma that normally ensure the proper functioning of melanocytes, which can be hindered when there is sun exposure from recreation and sunburns. This, in turn, results in the aberrant increase or multiplication of melanocytes. Melanoma may also result from alterations in cell behavior, which indicates that, as the incidence of this fatal skin disease rises, precautions about sun protection and avoiding prolonged sun exposure should be reinforced. To reduce the number of flamingos and encourage people to adopt appropriate skin care, one of the most crucial things that should be done is to develop proactive sun protection measures and public awareness campaigns. [6].

Melanoma is, just as any other cancerous disease, initiated when there are dysfunctional genetics behind normal cellulization, which leads to abnormal cellular multiplication. An undamaged cell does keep on developing beyond restricted growth because of this is the cause of cancer. Excessive UV radiation exposure is a major factor in DNA damage and is often connected to this procedure. UV light damage is particularly dangerous for melanocytes, which are specialized cells that make the pigment melanin. Documents indicate time and time again that the skin is the principal location of first tumor manifestation, which emphasizes the need for UV protection and preventive measures. Comprehending the process by which ultraviolet radiation triggers aberrant cellular activity, ultimately culminating in melanoma, underscores the paramount need of sun protection measures and prompt identification in ameliorating the consequences of this potentially fatal cutaneous ailment [7].

Melanoma proliferates along the epidermis in the event that the original tumor is not identified and treated. It spreads by penetrating the skin's surface and invading blood and lymph vessels. After a biopsy confirms the presence of melanoma, it is critical to identify the cancer's stage, which is divided into five categories (0 to 4). The determined stage is the only factor that determines the prognosis and treatment plans. Malignant cells in stage-0 melanoma are restricted to the skin's outermost layer, and lymph nodes are not involved in metastasis. Cancer cells grow to a maximum thickness of 2 mm in stage 1 melanoma, although they have not yet reached the lymph nodes. The melanoma's epidermis may or may not be intact, and the cancer cells may exhibit ulceration. Stage 2 is characterized by a breakdown of the original epidermis covering the melanoma cells, even if the lymph nodes are untouched. Phase 3, which is associated with regional dissemination and ensures ulceration, entails lymph node engagement. This stage contains four subclasses. The fourth and final stage is characterized by metastasis beyond local lymph nodes. At this point, the brain, lungs, and bones are among the vital organs at danger because the cancerous cells that cause melanoma have spread to other areas of the body. [6].

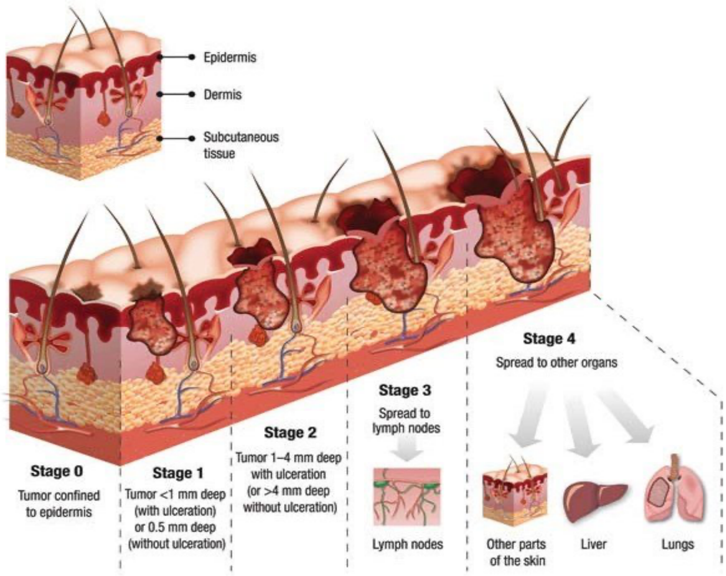

Figure 1. Different stages of skin cancer

Utilizing computer vision methods to recognize skin cancer is the subject of growing research, with a focus on dermoscopic images as an essential diagnostics device. Dermo copy is the process of taking close-up pictures of a skin portion using a magnifying lens and the right lighting. This method improves the visibility of skin patterns and features that could be signs of skin cancer. By enabling more precise and efficient early identification, the application of computer vision to skin cancer detection has the potential to revolutionize the field and ultimately improve outcomes for those who are at risk of the condition.[8].

The first stage in melanoma identification proficient methods is to take a digital photograph of the tissue. The technique most often used for this is called dermoscopy, or epiluminescence microscopy. Additionally, it makes it easier to encourage people to examine themselves for any questionable imperfections. The primary element of almost all technologies utilized for highly effective melanoma detection is still dermoscopy. [9].

Due to the increased exploitation of ML techniques, dozens of novel medical image analysis (MIA) applications have been invented nowadays. At first, Moldovan et al. employed the method using Gabor characteristics and multilayer deep neural networks, while using the threshold approach. Then the next stage will be to develop this result into a distinctive paradigm of melanoma skin cancer diagnosis which was given by a recent research. Such researchers' concept covers the domain of the Support Vector Machine model (SVM) by using some integration of good features extracted from the dermoscopic images, more precisely, the Histogram of Oriented Gradients (HOG). This kind of research emphasizes how machine learning algorithms can be used to improve the precision and efficacy of medical imaging-based skin cancer diagnosis techniques.[10].

2. Literature Review

In state-of-the-art healthcare, computer-aided diagnostic systems (CADs) cannot be done without, especially in the case of breast cancer diagnosis which is one of the most prevalent in the US. Melanoma, untreated form of skin cancer, has a tendency to disseminate across the epidermal skin layer, invading it and whiling proximity to blood vessels and lymphatic system. Early identification of melanoma as an effective treatment is an urgent challenge for researchers. An artificial intelligence data driven approach offers an alternative for skin cancer diagnosis which is smart and intelligent. Their purpose is to assign each and every image as part of training dataset to either "malignant" or "benign" categories though binary classification tasks which consists of feature extraction from images to eventually make them classified into given classes. By definition, a malignant skin tumor causing almost three-fourths of skin tumor-related deaths is Melanoma. Researchers also developed a method to help physicians diagnose skin lesions more accurately, classifying lesions into three categories: "melanoma," "abnormal," and "normal." classifiers created for the automated diagnosis of melanoma using the PH2 data set were employed in the diagnostic investigation. Several techniques, such as "Decision Tree (DT), K-nearest-neighbors (KNN), Support Vector Machines (SVM), and Artificial Neural Network (ANN)," were utilized to compare the findings of different research projects. The categorical variables used in this investigation were encoded using "one-of-N coding." It was discovered through k-fold cross-validation trials that the optimal values for "k" were 5 and 10. The results demonstrated that ANN outperformed other methods in class identification.[11].

A deep learning model becomes more sophisticated and complex as its number of layers rises. Deep learning performs remarkably well because of its increased complexity, which makes it an innovative tool for medical diagnostics. Deep learning's enormous applicability in medical contexts is shown by its layered architecture and prowess in pattern recognition and feature identification. Deep learning offers a promising path for accurate and efficient diagnoses in the complex field of healthcare by utilizing its natural ability to accurately identify tiny traits and complex patterns [11] .

With the use of deep learning algorithms, the classification of skin lesions has significantly advanced in recent decades.[36]. However, while working with small datasets, the challenge becomes more and more difficult for pioneering deep learning investigations in medical diagnostics. This difficulty is largely caused by deep learning algorithms' significant reliance on training data volume. A significant amount of labeled data and millions of parameters are required for these algorithms to learn and generalize well. [14].

Since deep learning models need to dedicate a large portion of their resources to training, an inadequate amount of data might lead to overfitting issues in these models. When a model finds it difficult to generalize to new data, overfitting happens. Researchers have conducted numerous efforts to address the limitations brought about by an insufficient data to develop deep learning models. Techniques like data augmentation are employed in these investigations [16].Transfer learning is another strategy used to address the issue of inadequate data for deep learning model training [14]. In the analysis, a variety of classifiers are also employed [15]. A synopsis of relevant studies and current methods for classifying skin lesions can be found in the sections that follow.

Table 1. A summary of the literature review

Reference	**Year of Paper**	**Used dataset**	**Method employed**	**Finding**	**Future work**
[17]	2018	HAM 10000	CNN	Our dermato-scopic image analysis performs better on a large dataset than the baseline that was taken into consideration, according to the provided techniques.	A variety of transfer learning strategies based on tuned CNNs will be developed and assessed in subsequent research.
[12]	2017	PH2	DT, KNN, SVM, and ANN.	The outcomes show that dermatologists can diagnose skin lesions with the aid of a medical decision support feature integrated into the	This work may progress even farther by utilizing a variety of preliminary data processing techniques and

				system created for this study.	hybrid classification algorithms. Moreover, this study can be combined with related image processing techniques to provide autonomous judgment in several medical fields.
[18]	2014	Using spectroscopic equipment, a total of 187 photos 19 of malignant melanoma and 168 of benign lesions were taken in a clinic.	k-NN, ANN, and NB.	This study describes an automated and accurate computer-assisted method for diagnosing melanoma.	We intend to conduct follow-up research in the future by obtaining more real data, particularly from melanoma cases, in order to evaluate our methodology in greater detail.
[19]	2018	The UCI Machine Learning Repository contains 116 datasets from actual life.	deep neural networks	Researchers show that deep neural networks can prevent overfitting and still obtain higher classification accuracy in this scenario.	Subsequent research ought to examine the connection between generalization and decorrelation and pinpoint a mechanism behind the observed decorrelation.
[20]	2018	RGB images of skin cancer are collected	CNN	Clean, widely accessible squamous cell carcinoma datasets are uniform and	The focus of our upcoming study will be on adding more types of skin

		from the internet.		yield dependable, consistent outcomes.	cancer to the ABCD (asymmetry, border, color, and diameter) rule-based method for classifying skin cancer.
[21]	2016	PH2	RF	Dictionary learning approaches give discriminant descriptors and encode strong structures of dermoscopic pictures.	Prospects for further investigation include contrasting Models for Bags of Words using sparse learned dictionaries.
[22]	2018	MNIST picture collection.	CNN-INTE, CNN, Meta-learning.	The interpretation is made possible by employing meta learning to find the relationships between the learnt hidden layer (referred to as "fc1") and the original training data.	We intend to start quantifying the interpreted results in our next study.

3. Materials and Methods

3.1 Datasets

For computer-assisted tools to understand the nuances of the current work, large datasets are essential. A dataset with lots of features is necessary to evaluate the efficacy of these troubleshooting instruments and guarantee that the network is gathering the most relevant and varied data. But historically, the lack of diversity and poor quantitative quantity related to cancer datasets have made it difficult to integrate artificial networks into cancer research. Artificial intelligence (AI) networks have to overcome this limitation and comprehend the intricacies of varied tumor-related data by either creating synthetic data or adapting for few-shot learning, as the amount of available data cannot be expanded. An overview of datasets which have impacted AI network' development since their creation is given in Table 2 Since the designs trained on the HAM10000 dataset will be the main focus of this research, a detailed explanation of them will be provided later in this section.

Table 2. Table of Datasets

The Dataset's Name	Year of Publication and Updates	Number of Pictures
DermQuest	1999	22082

AtlasDerm	2000	1024
ISIC archive	2016-2020	25331
Dermnet	1998	23000
HAM10000	2018	10,015
DermIS	-	6588
PH 2	2013	200

3.1.1. HAM10000

Ten thousand dermoscopy images of skin lesions make up the dataset named "human-against-machine" is made available to the public. These images were acquired from two distinct locations: The dermatology department at Medical University of Vienna, Austria, and Cliff Rosendahl's skin cancer clinic in Queensland, Australia. A 20-year period's worth of photographic scans of lesions were used to build this dataset.

Next, with a Nikon scanner, 8-bit JPEG images were created and resized to 800 × 600 pixels at 72 DPI. The dataset uses a variety of collection techniques and cleaning techniques to incorporate data from eight distinct categories in order to handle the diversity challenge. The data was gathered using devices such the analog cameras DermLite Fluid, DermLite HD, MoleMax HD, and DermLite Foto (3Gen).

The HAM10000 dataset is described in detail in Table 3, In addition to its subdivisions.

Table 3. A summary of the HAM10000 dataset.

Type of Skin lesion	Number of Pictures
Melanomas	6705
Nevi, the melanocytic	1113
Dermatofibromas	115
Keratoses Actinic	327
Lesion on Vascular Skin	142
Cancer of the basal cell	514
Innocent Keratoses	1099

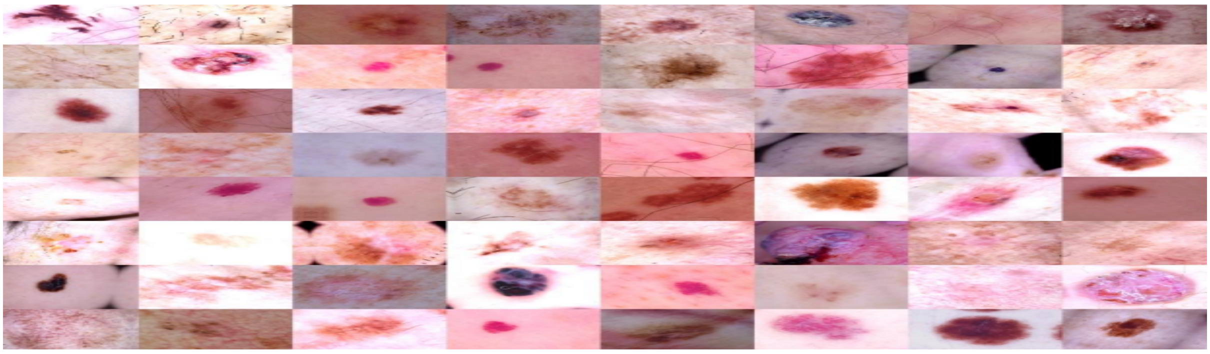

Figure 2. Pictures connected to the HAM10000 collection.

3.2. Setup for an Experiment

In the stage of research project experimentation, the needed machine was a laptop based on the Intel Core i5_4310U CPU with 16GB of RAM and a 16GB P100 GPU. The experiments were executed with Python 3.6.9 in Jupyter notebook environment, which was provided by Colab on Google. Figure 3 is the schematic illustration which outlines the methodology of coinage of the model to give the determination if the pathology of skin cancer has occurred or not.

3.3. Software libraries deployed

For the computer part of the experiment, we opted to build the experiment's code on top of PyTorch that has a good reputation for providing code that is easy to understand and for fast computing. Overlapping with Rapids CUML, Tensorflow-CPU was first utilized in the project stage as a coding environment for early trials version control, pandas, NumPy, SciPy, matplotlib, and sci-kit learn tool know stack also belong to this library.

3.4. Experiment 1. InspectionResNetV2

The results of the deployment of InspectionResNetV2 are astounding, with an accuracy rate of 96.4%. This precision highlights the model's ability to generate accurate predictions across the dataset and demonstrates how well it can represent complex patterns.

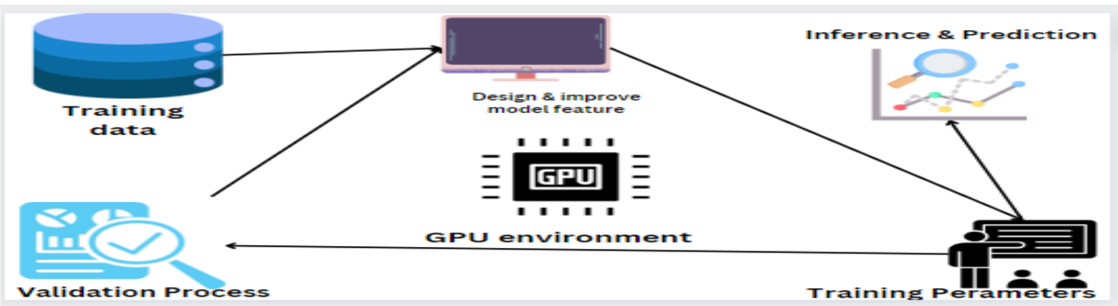

Figure 3. Experimental setup

This model further fits this picture with a true positive rate of 96.3%, which means that its presence is vividly manifested in the general demonstration of the model's capability to identify highly relevant cases or facts and filter through a large set of input data at an equally commendable rate. In addition, the model demonstrates a 98.6% specify and thus has the capability to accurately pick negative examples and distinguish unrelated patterns only. The model is good provides a wide range of possibilities with excellent specificity and sensitivity. This translates into a reliable classifier for a variety of tasks.

Ultimately, the interplay of all the elements confirms that InspectionResNetV2 is effective, further emphasizing its suitability for real-world tasks where highly accurate and consistent expectations are paramount. The model exposes how it acts wisely under those situations which require exceptional accuracy and aptness. Thus, we have a clear understanding of not only the beneficial but also the bad conditions surrounding us. In the picture classification matters, InspectionResNetV2 could be a nice instrument. It provides a holistic care for the applications that needs exact pattern recognition and classification.

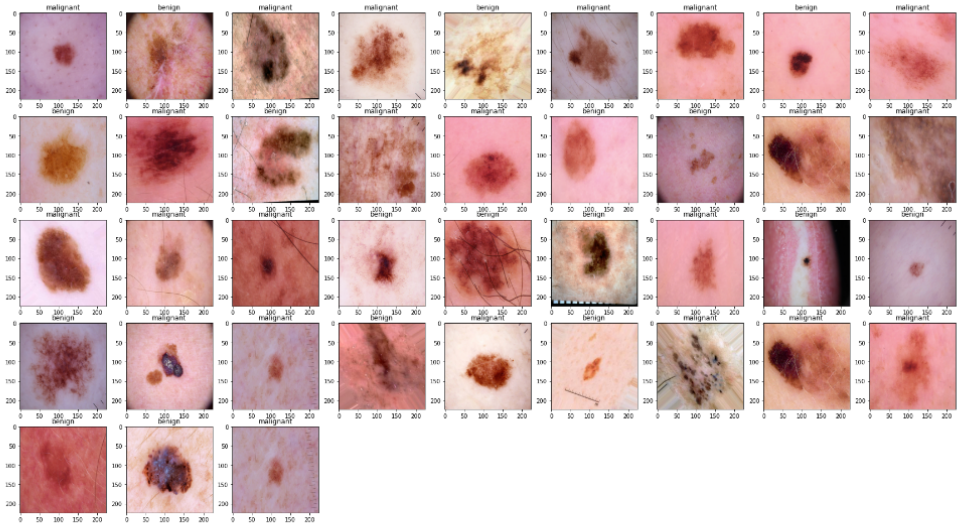

Figure 4. The 3D simulation of global warming using images as the media to visualize.

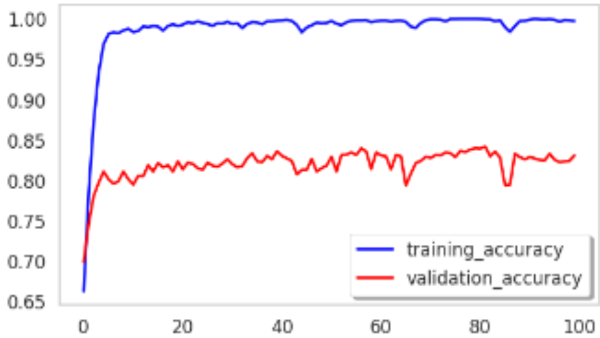

Figure 5. Model Precision

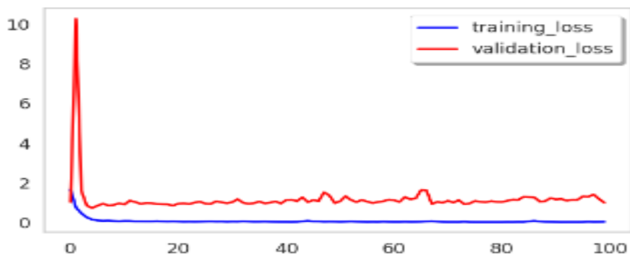

Figure 6. Loss of Model

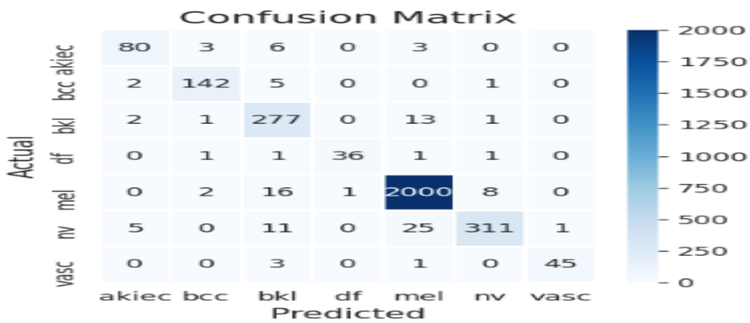

Figure 7. Confusion Matrix for InspectionResNetV2.

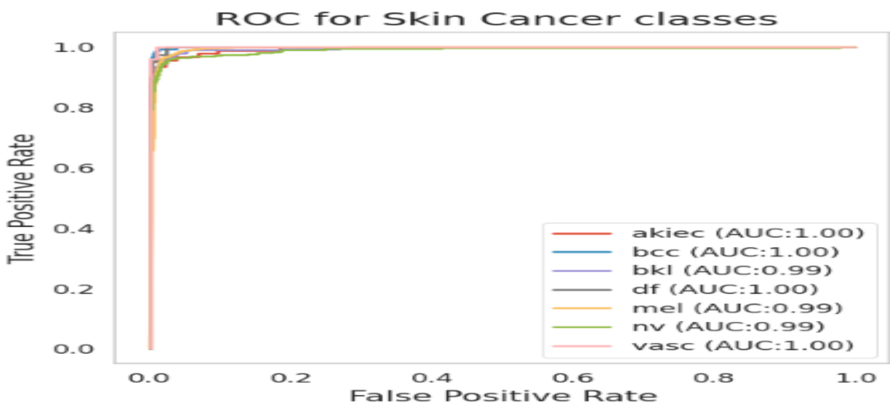

Figure 8. ROC Curve for Classification of Skin Cancer.

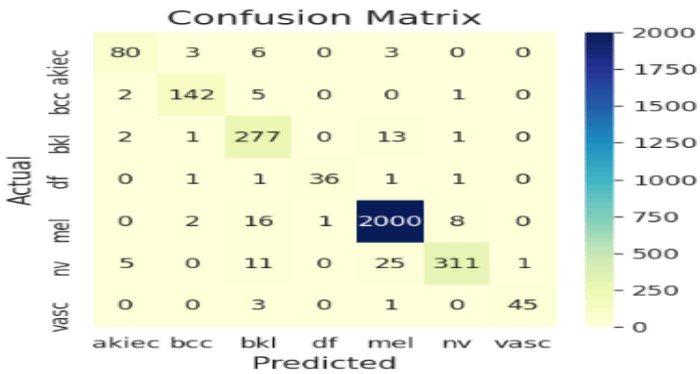

Figure 9. Tables of confusion.

3.5. Experiment 2. DenseNet201

Cell-wise connections have helped to provide DenseNet201 with outstanding effects as 97.4% accuracy has been recorded. This enhanced accuracy on the part of the model draws a comparison to how well it captures the nuances and details in the whole dataset and shows the extent of its ability to detect even the most subtle differences. The model's acute sensitivity towards vital data variables is made more evident in that, it possesses an average sensitivity for positive cases of 98.8 percent. Moreover, the focus on everyday life and at the same time the high accuracy in the detection of the negative situations, as well as in the exclusion of non-significant patterns, makes this model unique. Conclusively, DenseNet201's impressive balance between sensitivity and accuracy makes it a robust pretender on any classification tasks, not forgetting the ability to detect discernment and accuracy. The model has the ability to learn by example by acquiring a broad understanding of both kinds of examples. Its accuracy combined with dependable predictions makes it an effective and robust tool for classifying data. DenseNet201 can be considered as a superior option for practical image classification assignments wherein precise classification and fine pattern detection are the dominating competitive forces because of its goodness. Therefore, it can be concluded that this application substantiates DenseNet201 as a breakthrough response that has the capability to give quality greater than just in regular classification cases and also in problems classification cases.

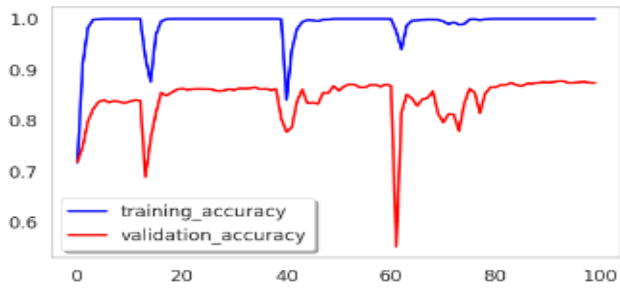

Figure 10. Model precision

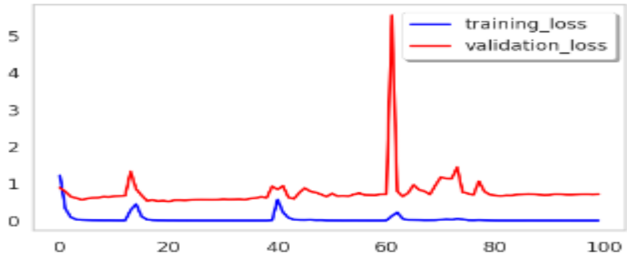

Figure 11. Model depletion

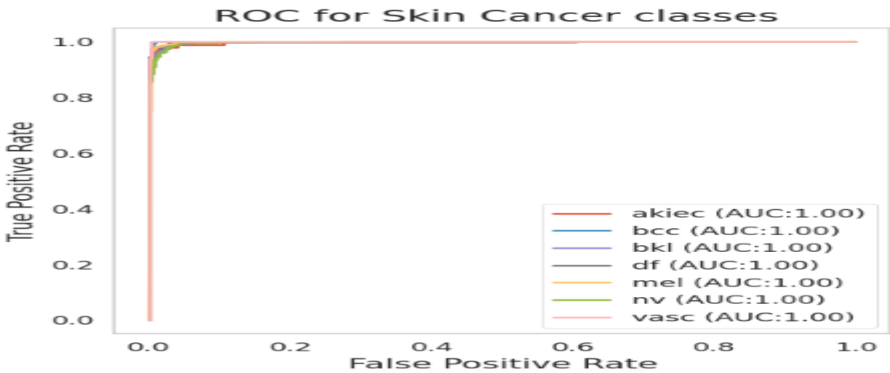

Figure 12. ROC for skin cancer

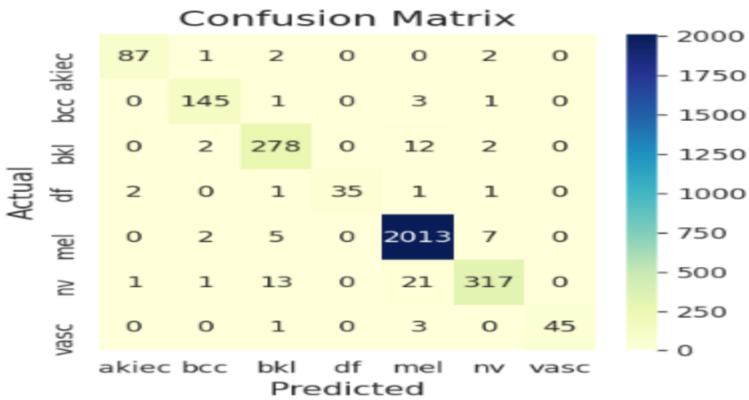

Figure 13. Confusing matrix

Figure 14. Comparison Of InspectionResNetV2 and DensNet201

4. Conclusions

The present paper offers a groundbreaking pipeline dubbed Skin CAN AI to help dermatologists with the difficult task of early identification of potentially dangerous skin abnormalities and essential decision-making during the diagnosis of skin cancer. By enhancing the training metrics of the suggested DenseNet model for skin lesion classification and making it easier to create simulated skin lesion data samples, the Skin-CNN model addresses the issue of limited dataset availability. Although generative adversarial networks have been tried in the past by the scientific community, their high processing power requirements and instability during training have made them unsuitable for use in clinical settings. However, the proposed design circumvents these problems by requiring a high computing capacity for both training and inference, allowing the method to effectively gain knowledge from a small dataset. Two frameworks based on transfer learning are currently available for computer-assisted mole diagnosis in skin cancer cases. The remaining five skin disease categories were to be classified in addition to the conventional nevi and melanoma categories. Two popular convolutional neural networks were optimized to be integrated into two proposed frameworks: a basic two-level hierarchical model and a two-level hierarchical model with a second level that can discriminate between images of benign and malignant moles. These frameworks were developed by utilizing the HAM10000 dataset. The trials revealed that DenseNet201 was the most effective deep network, outperforming the other networks by about 10%, especially in recall, a critical criterion for reducing false negative detections in medical diagnosis. In both binary and seven-class categorizations, the plain model performed quite well, achieving approximately 95% accuracy over the full HAM10000 dataset. Even with the use of data augmentation, the unbalanced dataset and inadequate images made it difficult for DenseNet201 to generalize in the second-level classifier, which affected the performance of the model as a whole. Interestingly, to enable a fair comparison of the deep networks' performances under the same parameter settings, the same setup was applied to each one. Deeper networks and other hierarchies will be investigated in future studies, as well as preprocessing methods to improve distinction between the six non-nevi categories. Developing suitable classifiers will require a detailed analysis of each class's features, and a promising direction for future research will be the use of probabilistic methods to the reliable prediction of various classifiers

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