

Face Skin Disease Classification Using Deep Learning Method (FSDC-DLM)

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Abstract

Digital technology has greatly improved the detection and diagnosis of skin disorders affecting the face, including cancer and gum disease. Before training the model, we used a number of data pretreatment and augmentation procedures to make it more effective. Rosacea, eczema, basal cell carcinoma, acne, and actinic keratosis were among the skin disorders that the researchers hoped to identify by applying the Deep Learning Method (InceptionResNetV2). The recommended InceptionResNetV2 model achieves a higher accuracy rate than current best practices, at 98.05%.

Keywords: Face Skin Diseases; Deep Learning; Face Skin Diseases; InceptionResNetV2.

I. INTRODUCTION

One of the most commonly observed types of infectious disease in the world today is a skin disease. Direct exposure to ultraviolet radiation, such as that from certain forms of high-frequency wireless devices used over extended periods of time, can produce physical changes that eventually manifest as cancer of the skin. More than 3.3 million non-melanoma cases, including basal cell carcinoma and squamous cell carcinoma, are examined among 5.4 million people in the United States each year [1]; new melanoma cases are anticipated to exceed 91,270 in 2018. Cancers of the skin, breast, lung, prostate gland, and colon, among others, are increasing in frequency year [2]. In addition, studies have found that 20% of U.S. citizens will develop skin cancer at some point [3]. Skin disease symptoms are complex, as they change over time and only manifest in select parts of the skin, making accurate diagnosis difficult. Several indicators can be used to identify skin diseases, including the location, size, shape, color, and distribution of lesions. Correctly diagnosing melanoma skin cancer typically involves using one of four major medical diagnosis procedures, including the ABCD rules, the Menzies method, the 7-Point Checklist, and pattern analysis, any one of which can make the detection process fairly hard by analyzing certain components independently [4]. The diagnosis of skin cancer is greatly improved by using any

of these techniques. Unlike human specialist diagnoses, which rely on individual opinion and may be hardly reproducible [6, 7], distinguishing skin lesions [5] requires an extremely high level of ability. Using the usual feature extraction method with well-known classifiers like SVM and ANN has improved the efficiency and performance of computer-assisted diagnostics. Diagnostic methods [8]-[10] are highly effective for melanoma (a form of skin cancer), but they fail when used for other types of skin diseases.

Dermatoscopy is the preferred imaging technique for removing undesirable surface reflections. Deeper skin lesions can be detected, and their severity can be more properly measured when surface reflection is eliminated. Clinical trials have demonstrated that dermatologists using this technology outperform those using standard imaging in terms of diagnosis accuracy [11]. The future of healthcare delivery is bright, thanks to developments like automated dermatological diagnosis algorithms and the soon-to-be-available, inexpensive dermatoscopy equipment that can be connected to smartphones [12].

Prior computer-assisted methods for dermatological picture categorization had two major drawbacks. For starters, there is a lack of information [13]. Secondly, there are a lot of obstacles with the imaging process itself, since skin photos were taken using dermoscopy and

histology, and biopsy images were taken using a microscope and a biopsy [14]. Classification algorithms for skin cancer images in the past relied heavily on segmentation, pre-processing, and feature extraction [15].

Using high-end, consumer-grade cameras, automated detection systems have recently become more common. Both desktop and mobile users can benefit from this framework, which serves as a telemedicine tool and, more importantly, a help to doctors. By applying deep learning algorithms, we can bypass the tedious feature extraction process, which will save us a lot of time and energy. The patient is alerted to any worrisome signs, which saves time. We have built a powerful and effective deep-learning method to help dermatologists detect skin cancer early and administer treatments quickly. Building these structures requires deep learning models trained on a massive dataset of expert-annotated images of benign and malignant melanoma skin cancers. Through the use of trained deep learning networks, doctors can identify the type of skin lesion and predict its spread from photographs of the lesions [16].

Face skin disease image classification calls for highly trained specialists. In practice, however, specialized dermatologists are still required to physically examine patients' faces to classify skin diseases. This is because a large portion of the prior work in automation relied on unsupervised/supervised learning approaches, which necessitate an enormous amount of pictures for training, and have a high false negative rate. The majority of methods have restricted their use to a subset of available data. Until far, datasets for imaging skin diseases on the face have not taken into account patient-level data collected from several skin lesions on the same individual. Although they might be effective, the current categorization methods are inefficient due to their low accuracy and the system's lack of resilience. Consequently, a fresh strategy to tackle these problems is suggested in this study. For accurate facial skin disease image categorization, the proposed method employs deep learning.

The primary objective of this study is to create a system that can detect and differentiate between acne, rosacea, basal cell carcinoma, eczema, and actinic keratosis automatically. Fatal problems are caused by the delayed therapy. Both sexes are disproportionately affected by skin cancer, with facial skin disease being the deadliest kind. This highlights the significance of identifying and treating facial skin problems at an early stage. Comparatively, skin cancer has a far greater mortality rate than other cancers. Following the main contributions of this research:

- Developed a deep learning method to classify the face skin disease images.
- To enhance the performance of the existing models in terms of accuracy.
- To analyze the issue of an imbalanced dataset in the context of classification.

- To develop a method to overcome the issues of a high false-negative rate.

II. LITERATURE REVIEW

Over the past few years, deep CNNs have become vastly more popular than feature learning and image categorization. Training a network on a massive dataset with a high-performance GPU yields impressive results. Multiple studies [17], [18], and [19] conducted on ImageNet [20] demonstrate that classical approaches utilising deep CNN achieve superior performance to humans in object categorization.

Recent work by Esteva et al. [21] has optimised the VGG16 and VGG19 architectures to create a skin disease classification system that can be used for any skin condition. Top-1 categorization accuracy for their network was 60.0%, and for Top-3 accuracy, it was 80.3%, greatly outperforming social skills in their studies. They advocated using a similar strategy to boost performance.

However, there is also encouraging progress being made in the field of deep learning as it relates to disorders of the face. More than 200 genetic diseases may be identified from facial photos with reasonable accuracy thanks to the work of a deep learning algorithm called DeepGestalt, developed by the researchers cited in [22]. Researchers in Reference [23] studied the use of CNNs to categorise acne into mild, moderate, and severe forms; their findings demonstrate that their system outperforms human dermatologists in terms of accuracy.

On a global scale, cancer ranks high among the most lethal diseases. The World Health Organization (WHO) predicts that 13.1 million individuals will succumb to cancer by the year 2030 [24]. In the US, skin cancer is more common than any other type of cancer [25]. Twenty percent of U.S. adults will develop skin cancer at some time [26]. Skin cancer is not necessarily fatal. But early detection is key to saving lives. To develop better ways for early detection and identification of this potentially deadly disease, research on human skin and different types of skin cancer is crucial.

Muhammad Qasim Khan et al. [27] suggested a way to differentiate melanoma from nevus. At first, the writer employed a Gaussian Filter to filter out the ambient noise. To fragment the lesion, K-means clustering was employed. The next step was to decouple the texture and color data using a hybrid super feature vector. To classify the data, Support Vector Machines (SVMs) were used. Using the DERMIS dataset, we tested how well the proposed strategy worked. In the collection, you can find 397 pictures of lesions; 146 of those show melanoma, and 251 show nevi. A very efficient model has been supplied. The suggested method had a success rate of 92.88%.

When caught early, 90% of skin cancers are treatable, but only 50% are if caught late [28]. Early detection of skin cancers and other skin diseases is now possible with more precision thanks to advancements in

high-resolution, non-invasive imaging technology [29]-[34]. Overtreatment (caused by erroneous positive diagnoses) and undertreatment (caused by false negative diagnoses) are both exacerbated by the declining diagnostic accuracy for melanoma. The majority of the increase in treatment costs is attributable to false positive diagnoses, which increase the risk of complications by leading to the removal of an excessive number of benign lesions for pathological assessment and biopsy. On the other hand, there is hope that high-resolution imaging technologies can increase diagnostic specificity, which could lead to fewer needless excisions and lower healthcare expenditures. Ultrasound, dermoscopy, optical coherence tomography, and reflectance confocal microscopy are the four most used imaging modalities to diagnose skin malignancies nowadays.

III. METHODOLOGY

➤ Materials and Methods

This study introduces a deep-learning approach for face skin disease classification. Classification of skin diseases affecting the face using a deep-learning approach is presented in this paper. In order to generate more distinct records and address class imbalance, a first-level augmentation and pre-processing stage is applied. After mechanical features were extracted to differentiate between Acne, Actinic Keratosis, Basal Cell Carcinoma, Eczema, and Rosacea from the face skin disease dataset, a pre-trained model named "Deep Learning Method" was applied at the second level. Figure 1 shows the steps involved in the suggested method's process flow.

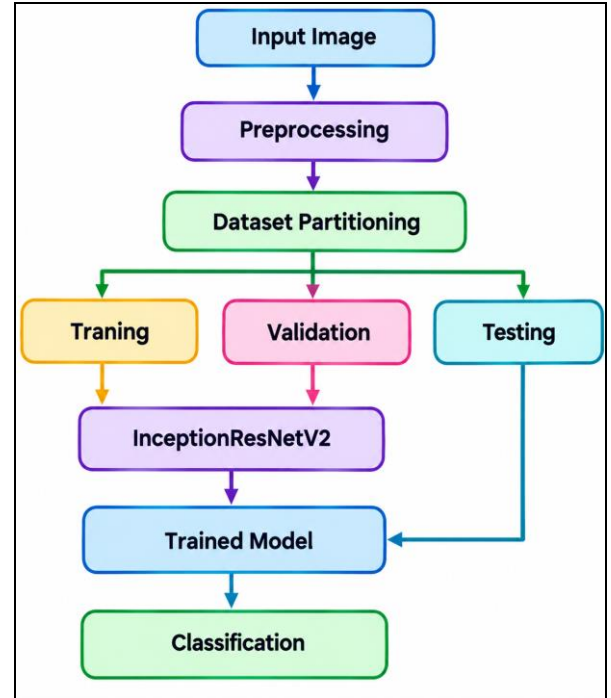


Fig 1 Flow Chart of the Presented Method.

➤ Face Skin Diseases Dataset

The most extensive collection of high-quality face skin disease images made accessible for study can be found in the Face Skin Diseases (FSD) dataset archive [35]. There are 625 images in the dataset, 128 images in each class. Figure 2 shows examples of the various classes. The pictures of the appropriate class were randomly picked from the entire collection.

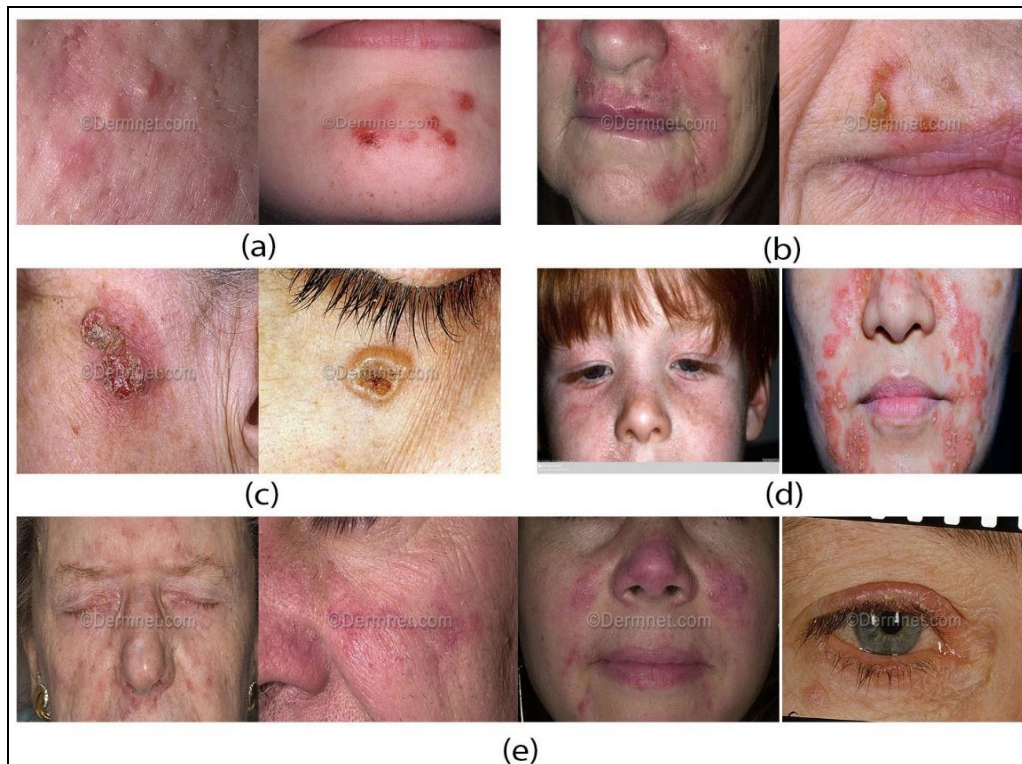


Fig 2 (a) Acne, (b) Actinic Keratosis, (c) Basal Cell Carcinoma, (d) Eczema, and (e) Rosacea classes of FSD dataset.

➤ Image Pre-Processing

Preprocessing is applied to all input photos of the FSD dataset to achieve increased consistency in classification results and enhanced feature extraction. A

massive image dataset was needed for the CNN approach's extensive training repetitions to avoid the risk of over-fitting.

➤ Image Resizing

There are 6000×4000 variations of each image in the trash dataset. The size of the dataset has been modified to be 224×224 . The model's performance will be severely reduced in exchange for halving the processing time.

➤ Training, Validation, and Testing

Using the dataset from the previous chapter, InceptionResNetV2 was trained from scratch. Training, testing, and validation comprised the FSD dataset. The validation and test datasets were used to evaluate the InceptionResNetV2 model, which was trained on the training set. Thus, we divided the dataset into 60% training, 20% testing, and 20% validation. FSD dataset

training, validation, and testing employed 16350, 3500, and 3500 photos, respectively.

The training set was augmented by rescaling, width shift, rotation, brightness, height shift, zoom range, shear range, horizontal flip, and channel shift with fill mode nearest to boost diversity and dataset size. Overfitting would be eliminated, ensuring model generalization. Model research used the Adam optimization technique. The present study used the FSD dataset training photos with 60% image ratios. Validation and testing each receive 20% of the remaining 40% of real photographs. InceptionResNetV2, the model was trained to categorize and predict class labels for every training image. The details of the FSD dataset summaries are in Table I.

Table 1 Summary of the FSD Dataset

Split	Classes	Label Samples	Total Samples
Training	Acne	75	375
	Actinic Keratosis	75	
	Basal Cell Carcinoma	75	
	Eczemaa	75	
	Rosacea	75	
Validation	Acne	25	125
	Actinic Keratosis	25	
	Basal Cell Carcinoma	25	
	Eczemaa	25	
	Rosacea	25	
Testing	Acne	25	125
	Actinic Keratosis	25	
	Basal Cell Carcinoma	25	
	Eczemaa	25	
	Rosacea	25	
Total			625

➤ Architecture of InceptionResNetV2 Base Model

A powerful tool for new tasks with inadequate labeled data has been the transfer learning approach of deep learning. Using the InceptionResNetV2 architecture, this research applies transfer learning to picture categorization challenges. By combining the finest aspects of the Inception and ResNet architectures, the InceptionResNetV2 model achieves a high level of accuracy and efficiency. This study will demonstrate how to utilize InceptionResNetV2 [36] for transfer learning by going over its inner workings. As shown in Figure 3.

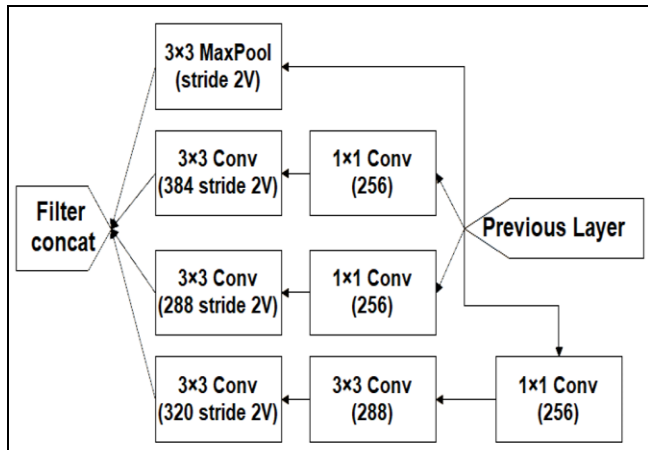


Fig 3 Architecture of the InceptionResNetV2 Model.

➤ Evaluation Measures

The testing dataset was used to evaluate the suggested approach following the training phase. We tested the architecture's efficacy using recall, accuracy, F1 score, and precision. We will examine the performance metrics utilized in this research in the parts that follow. What follows is a mathematical definition and representation of the terms "true positive," "true negative," "false negative," and "false positive."

• Classification Accuracy

The accuracy of a classification system can be evaluated by determining what percentage of its predictions were correct and what percentage were incorrect.

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

• Precision

When analysing the effectiveness of a model, classification accuracy may not always be the most appropriate metric to employ. For instance, this is one of the scenarios where there is a considerable gap in socioeconomic status. It's a safe bet to assume that each sample is of the highest possible quality. If the model isn't picking up any new information, it would be irrational to

infer that all components belong to the best class. Therefore, when we talk about accuracy, we refer to the fluctuation in findings you receive while measuring the same object several times with the same tools. The term "precision" refers to one of these statistics and can be defined as follows:

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

- **Recall**

Another critical parameter is called recall, and it refers to the percentage of input samples that are of a type that the model can accurately predict. The formula for the recall is as follows:

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$$

- **F1 Score**

The F1 score is a statistic utilised to contrast recall and precision.

$$\text{F1 Score} = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})$$

IV. RESULTS AND DISCUSSION

A Google Research team evaluated the InceptionResNetV2 model. This InceptionResNetV2

method experiment was built using Tensor-Flow, the free and open-source Keras, and Python. There was a default learning rate and a binary cross-entropy loss function used during training by the Adam optimizer.

- Face Skin Disease Classification using a Deep Learning Model (InceptionResNetV2) was observed using the FSD dataset to assess its efficacy.
- Evaluation of the presented InceptionResNetV2 model's performance on the FDS dataset using data augmentation techniques on the training set.
- The results were compared to those of other state-of-the-art networks.

➤ Performance of Proposed Model on FSD Dataset

Our proposal for an FSDC-DLM made use of the InceptionResNetV2 model. You can see the accuracy and loss for the InceptionResNetV2 base model during validation and training in Figure 4. A steady increase from 69.20 to 97.50 percent was the training accuracy of the model. In contrast, during the first epoch, the InceptionResNetV2 base model's validation accuracy was 86.48% and following the last epoch, it improved to 90.76%. With the last epoch out of the way, training loss dropped from 87.88 to 9.73 percent, while validation loss dropped from 75.61 to 10.10 percent in the preceding epoch.

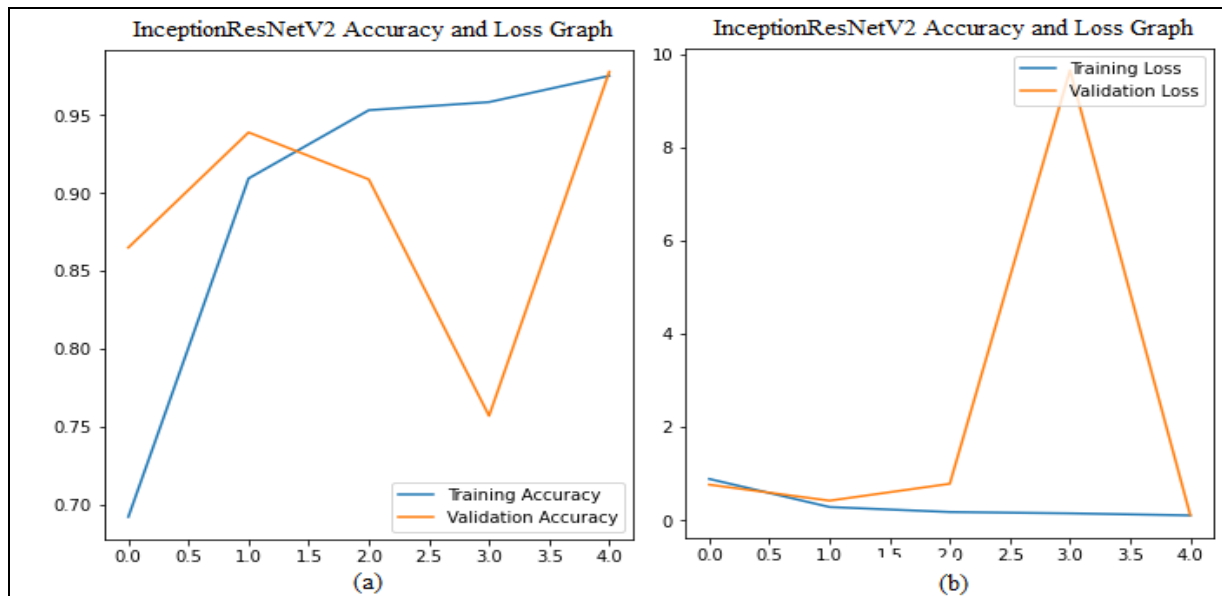


Fig 4 The InceptionResNetV2 Base Model: (a) Accuracy (b) Loss Graph.

Test set metrics, including recall, accuracy, precision, and F1 score, reveal how well the InceptionResNetV2 model performed. In contrast to Actinic Keratosis's 98% accuracy, 99% recall, and 98% F1 score, the Acne class only managed 95% accuracy, 97% recall, and 96% F1 score. For the Basal Cell Carcinoma class, the f1 score was 99%, recall was 97%, and precision was 98%. On the F1 score, recall, and precision, the Eczema group achieved a perfect score of 99%. The Rosacea group had an impressive 98% F1 score, 99% recall, and 96% accuracy. We find an average success rate of 98.05% across all courses in the test data.

Across all seven classes, InceptionResNetV2 performed exceptionally well, as can be seen from the results.

By examining the confusion matrix on the test set, we have examined the performance of InceptionResNetV2's fundamental model (see Figure 5). The outcomes showed that the InceptionResNetV2 foundational model attained an accuracy of 98.15% and a miss-classification accuracy of 1.95%. Figure 5 shows that out of the five picture classes, the second base model got them all right. The InceptionResNetV2 base model's remarkable accuracy is shown by the confusion matrix, which shows the accuracy of each class's categorization.

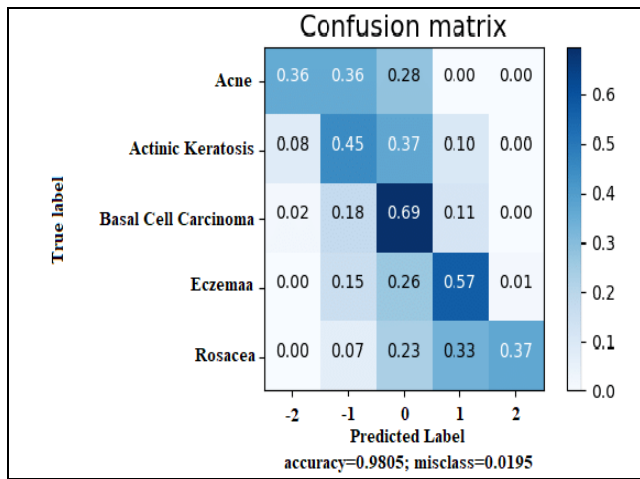


Fig 5 The InceptionResNetV2 Base Model Confusion Matrix on Test Set.

➤ Comparison of Proposed Method with State-of-the-art Methods

To prove that the new approach is applicable in a variety of contexts, we contrasted the suggested model's performance with that of cutting-edge algorithms. Results showed that the offered deep learning system outperformed the best state-of-the-art approaches. The proposed procedure should have been more at odds with the established norms. Using preexisting reported face skin disease categorization methods as a benchmark, the effectiveness of the developed method was evaluated.

In comparison to earlier studies, Arief Budhiman et al. [39] discovered that the accuracy rate of their suggested ResNet34 model was 83%. Although the ISIC 2018 dataset has a class imbalance and fewer images, it was nevertheless used to classify melanoma. Although it was more computationally expensive, Khan et al. [37] nevertheless managed to achieve a 93.40% accuracy rate. The ISBI-2016 dataset was utilized, which possesses a greater degree of unequal distribution of classes and fewer images. With the ISBI-2016 dataset, the hybrid framework developed by Jayapriya et al. [38] combines VGG 16 and GoogleNet, two FCNs, and obtains an accuracy rate of 88.92%. By achieving a 98.05% accuracy with fewer parameters and reduced computing cost, the proposed ResNet34 model surpassed state-of-the-art approaches.

V. CONCLUSION

Skin diseases affecting the face are becoming increasingly common each year. If this tumor is detected and treated early enough, it is very curable; the chances of survival and the risk of death both increase. In addition, because of physicians' inherent subjectivity and lack of experience, the current clinical methods for diagnosing skin illnesses are susceptible to human error. Therefore, more accurate and dependable methods are required, which would benefit both experienced and novice physicians.

This thesis introduced new and practical ways to assess abrupt cutoff and improve classification algorithms; these measures will reduce the amount of

false negative and false positive diagnoses and make visual viewing of dermoscopy images less subjective.

Research into skin disease issues utilizing deep learning has shown promising results when compared to more conventional methods, with the InceptionResNetV2 framework providing the best overall performance. These pictures were found on Kaggle. Acne, Rosacea, Basal Cell Carcinoma, Eczema, and Actinic Keratosis are some of the facial skin illnesses that the network is tested on. Acne, Rosacea, Basal Cell Carcinoma, Eczema, and Actinic Keratosis could all be identified in images when the model was trained. Using the InceptionResNetV2 architecture, we achieved a remarkable 98.05% accuracy for this endeavor. The lightweight InceptionResNetV2 technology is quickly becoming the standard for vision applications on embedded and mobile platforms that do not require figure control. The remarkable performance is probably due in part to the use of InceptionResNetV2 and the addition of layers and epochs.

This study draws attention to the significance of measuring performance adequately from the viewpoint of dataset imbalance, a topic that academics frequently ignore, in addition to focusing on network architecture. Present methods of evaluating networks may benefit from adding visual representations of network activations. Using this knowledge, the scope of the model's issues might be narrowed. The study's use of image gathering further added complexity. To get better results than comparable works, this one makes use of a larger number of pictures.

An issue was that more images could only be viewed with the proper permits. It is possible to enhance the InceptionResNetV2 model's classification of facial skin illnesses with minor adjustments in the medical field. The best way to classify skin diseases of the face and detect cancer is with deep learning.

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