Journal of Prevention, Diagnosis and Management of Human Diseases
ISSN: 2799-1202
Vol: 04, No. 01, Dec 2023-Jan 2024
http://journal.hmjournals.com/index.php/JPDMHD
DOI: https://doi.org/10.55529/jpdmhd.41.40.49

Skin Disease Detection Using Deep Learning Techniques

Mr. A. Venu Gopal[1*], Achanta Sai Hari Naga Pavan[2], Kandula Nagendra[3], Mandapati Pavan Sai[4], Andey Vijay Kumar[5]

[1]Assistant Professor, Department of Information Technology, India.*
[2,3,4,5]Department of Computer Science and Business Systems, Vishnu Institute of Technology, Andhra Pradesh, India.

Corresponding Email: [1]venugopal.a@vishnu.edu.in*

Received: 29 September 2023 **Accepted:** 18 December 2023 **Published:** 31 January 2024

***Abstract:** The effectiveness of deep learning methods in the identification of different skin illnesses is investigated in this article, with a focus on the VGG19 and Inception ResNetV2 frameworks. Leveraging the advanced features of VGG19 and Inception ResNetV2, the model is adept at processing intricate visual inputs, exhibiting particular strength in discerning subtle differences in texture, color, and form associated with diverse skin conditions such as dermatitis, eczema, psoriasis, nail fungus, and melanoma. The implementation of the deep learning architectures further enables the extraction of complex characteristics critical for accurate diagnosis. The model is trained on a wide range of datasets covering a wide range of skin conditions. Transfer learning greatly improves the model's performance, especially in situations where there are few labelled datasets. This innovative approach holds great promise in revolutionizing dermatological diagnostics, offering a precise and automated means of diagnosing skin illnesses. The potential for early identification and intervention stands to significantly improve patient outcomes in the field of dermatology.*

***Keywords:** Dermatological Diagnostics, VGG19, Inception ResNetV2, Early Detection, Heterogeneous Dataset, Healthcare.*

1. INTRODUCTION

The use of deep learning methods into medical imaging applications in recent years has shown significant promise for revolutionizing diagnostics and illness detection. The area of dermatology has the potential to greatly benefit from the capabilities of deep learning models within this framework. This work focuses on the use of the VGG19 and Inception ResNetV2 architectures for detecting skin diseases, with the goal of addressing the challenges involved in diagnosing various dermatological problems. Given the diverse and complex nature of skin

Journal of Prevention, Diagnosis and Management of Human Diseases
ISSN: 2799-1202
Vol: 04, No. 01, Dec 2023-Jan 2024
http://journal.hmjournals.com/index.php/JPDMHD
DOI: https://doi.org/10.55529/jpdmhd.41.40.49

disorders, it is crucial to have precise and efficient diagnostic techniques to accurately identify them. Deep learning models, like VGG19 and Inception ResNetV2, with their sophisticated feature extraction capabilities, provide a hopeful approach to automate the detection process and enable prompt responses.

The integration of deep learning methods in dermatology goes beyond simple categorization; it signifies a fundamental change in the approach to diagnosing and treating skin problems. Through the use of VGG19, a potent model renowned for its capacity to gather both local and global data, this work seeks to improve the development of a trustworthy and automated skin disease detection system. These breakthroughs have the potential to completely transform the sector by enabling early identification and customized treatment strategies, and enhanced patient outcomes. The integration of VGG19 into skin disease detection is a major advancement in healthcare solutions, meeting the increasing need for efficient and accurate diagnostics. This integration not only marks a technical milestone but also a step towards more effective and patient-centric dermatological diagnostics.

Significance

In the fields of dermatology and healthcare, the proposed skin disease detection system's use of deep learning techniques is highly significant. Several crucial factors underscore the significance and potential influence of this research:

Early Identification and Therapy

Automating the detection of skin diseases allows for early diagnosis, which is crucial for effectively treating different dermatological problems. Prompt care can greatly enhance patient outcomes and mitigate the likelihood of complications linked to late stages of illnesses like melanoma.

Access and Cost

Utilizing deep learning techniques to automate the diagnostic procedure can effectively resolve the problem of limited accessibility to dermatological knowledge. The suggested system provides a cost-effective and efficient alternative for initial screening of skin diseases in places with limited access to specialist healthcare practitioners.

Enhancing Efficiency in Dermatological Practices

Dermatologists encounter a significant amount of labour, and an automated system can be a useful tool for making the diagnostic procedure more efficient. The method aids healthcare workers in detecting possible skin problems, enabling dermatologists to concentrate their knowledge on more intricate situations, therefore enhancing overall efficiency in dermatological practices.

Impact on Public Health

Implementing an automated skin disease detection system on a large scale can significantly improve public health. The system enables individuals to conduct first self-assessments by offering a user-friendly interface, hence boosting awareness and motivating proactive health steps among the general public.

Decrease in Rates of Incorrect Diagnosis

Errors made by humans in the process of diagnosing skin disorders might result in the incorrect interpretation and diagnosis of such conditions. Utilizing deep learning models, which have been trained on a wide range of data, can improve precision and decrease the probability of mistakes, hence bolstering the dependability of the diagnostic procedure.

2. RELATED WORK

The current focus on VGG19 is based on recent studies that looked at the application of deep learning algorithms for skin disease identification. Promising outcomes have been observed in the automation of dermatological illness diagnosis through the use of convolutional neural networks (CNNs) in research. Scientists have used many structures, including VGG16, Inception, and Dense Net, to demonstrate their effectiveness in reliably detecting skin illnesses using picture analysis. These results emphasize the need of using deep learning models to improve diagnostic accuracy and provide the possibility for comparing VGG19 performance in detecting skin diseases.
Additionally, transfer learning techniques are becoming more and more common in dermatological research as a way to overcome the challenges brought on by a lack of annotated datasets. Scholars have examined the application of pre-trained models using large image datasets to enhance the capacity of deep learning algorithms to recognise skin conditions. Since the pre-trained weights on large picture datasets are used to improve the model's performance on dermatological photos, the present study's method of adding VGG19 is consistent with this paradigm. In addition to using VGG19, the application of transfer learning techniques demonstrates a larger trend in the literature emphasizing the value of leveraging pre-existing data to improve deep learning models' diagnostic capabilities for skin conditions.

Proposed System

Skin conditions can be difficult to diagnose and treat, frequently requiring specialized knowledge to provide a precise diagnosis. By utilizing developments in deep learning, researchers have investigated the possibility of neural network designs in automating the diagnosing process. In this study, we investigated the diagnostic efficacy of two popular deep learning models for skin disease identification: VGG19 and Inception ResNetV2. Our study's goal was to determine whether particular model performed better at accurately classifying skin conditions. This would provide valuable assistance to dermatologists and healthcare professionals in promptly and effectively diagnosing such conditions. To evaluate the effectiveness of VGG19 and Inception ResNetV2, we built a thorough dataset of photos depicting a range of skin disorders, such as eczema, psoriasis, dermatitis, and melanoma. The purpose of our investigation was to find out which model was more accurate at categorising skin problems. VGG19 and Inception ResNetV2 used transfer learning on ImageNet to use pre-trained weights and accelerate convergence. Using the information on skin diseases, we adjusted the models and contrasted them according to metrics like accuracy, precision, recall, and F1-score.

Journal of Prevention, Diagnosis and Management of Human Diseases
ISSN: 2799-1202
Vol: 04, No. 01, Dec 2023-Jan 2024
http://journal.hmjournals.com/index.php/JPDMHD
DOI: https://doi.org/10.55529/jpdmhd.41.40.49

In skin disease classification, we discovered that VGG19 performed better than Inception ResNetV2. In terms of accuracy, precision, and recall, VGG19 performed better than Inception ResNetV2 when tested on a range of skin conditions. The enhanced efficacy of VGG19 can be ascribed to its more profound structure and capacity to capture subtle characteristics inherent in skin photographs. In addition, VGG19 demonstrated strong generalization ability by consistently performing well on new and unknown data. These results show that deep learning models, especially VGG19, can automate skin disease diagnosis. These models can aid dermatologists in making well-informed decisions and enhancing patient outcomes by precisely detecting skin problems. Deep learning techniques are promising for dermatology difficulties such as restricted access to specialist experts and rising skin disease rates due to their scalability and adaptability.

Objectives

The goals of the proposed skin disease detection system, using the VGG19 architecture, are diverse and complex. The primary objective of the system is to deploy and enhance the VGG19 deep learning model, using its sophisticated residual learning architecture to efficiently extract features from dermatological photos. The goal is to use the capabilities of VGG19 in identifying complex patterns and changes that are characteristic of various skin disorders. Furthermore, the system aims to use transfer learning methodologies by refining VGG19 using pre-existing weights obtained from a diverse picture collection. The objective of this technique is to increase the model's capacity to adapt to the unique features of dermatological pictures, hence promoting better generalization and diagnosis accuracy. Finally, the primary goal is to develop an extensive and varied dataset that includes a wide range of skin conditions. This dataset is essential for training advanced models, allowing the system to reliably recognize and categorize a wide range of skin disorders. As a result, it greatly enhances the diagnostic capabilities in the field of dermatology, leading to more effective and exact diagnoses.

3. METHODOLOGY

Dataset Collection and Preprocessing: We collected a diverse dataset comprising images of various skin diseases, including eczema, psoriasis, dermatitis, melanoma, and others, from publicly available sources and dermatology databases. The dataset was pre-processed to ensure consistency in image size, resolution, and quality. Images were resized to a standard dimension and normalized to enhance model performance.

Data Augmentation: We altered the photographs in the dataset by rotating, flipping, zooming, and shifting in order to diversify it and enhance its quality. Through exposure to a greater variety of variances in the input data, data augmentation helps prevent overfitting and enhances the models' capacity to generalize.

Model Selection and Architecture: We have chosen two cutting-edge deep learning models, VGG19 and Inception ResNetV2, for our comparison study. Convolutional neural network (CNN) architecture VGG19 is renowned for its efficiency and simplicity in image

Journal of Prevention, Diagnosis and Management of Human Diseases
ISSN: 2799-1202
Vol: 04, No. 01, Dec 2023-Jan 2024
http://journal.hmjournals.com/index.php/JPDMHD
DOI: https://doi.org/10.55529/jpdmhd.41.40.49

classification applications. Inception ResNetV2 is a more complex architecture that combines the advantages of the Inception and ResNet architectures, featuring both parallel and residual connections.

Transfer Learning: We employed transfer learning techniques to leverage the pre-trained weights of VGG19 and Inception ResNetV2 on the ImageNet dataset. Transfer learning allows us to benefit from the learned features of models trained on large-scale datasets, thereby accelerating convergence and improving performance on our skin disease dataset.

Model Training and Evaluation: To train and assess the models, the pre-processed dataset was divided into training, validation, and test sets. Using the training data, we adjusted the pre-trained VGG19 and Inception ResNetV2 models, and we kept an eye on how they performed using the validation set. Metrics including accuracy, precision, recall, and F1-score were used to evaluate the performance of the models in order to determine how well they could categorize skin conditions.

Comparative Analysis: We conducted a comprehensive comparative analysis of VGG19 and Inception ResNetV2 based on their performance metrics. The models were evaluated on their ability to distinguish between different skin conditions and provide accurate diagnoses. Statistical tests were performed to determine if the performance differences between the models were statistically significant.

Conclusion: To sum up, our comprehensive approach offers valuable perspectives on the procedure of evaluating deep learning models' efficacy in diagnosing skin conditions. With the use of cutting-edge architectures like VGG19 and Inception ResNetV2, along with transfer learning, we hope to further the progress of precise and effective dermatology diagnostic instruments. Our comparative analysis will help dermatologists and healthcare professionals make informed decisions about the adoption of deep learning technologies in clinical practice.

Dataset: The International Skin Imaging Collaboration (ISIC) provided 2357 photographs of benign and malignant oncological disorders for the dataset. With the exception of melanomas and moles, which are somewhat more common, the photos were evenly split into subsets and categorized using the ISIC classifications. Actinic keratosis, Basal cell carcinoma, Dermatofibroma, Melanoma, Nevus, Pigmented Benign Keratosis, Seborrheic Keratosis, Squamous Cell Carcinoma, and Vascular Lesion are among the disorders included in the dataset. The dataset comprises images that have been labelled with one of these disorders, making it possible to train and assess machine learning models for the detection and classification of skin diseases.

Journal of Prevention, Diagnosis and Management of Human Diseases
ISSN: 2799-1202
Vol: 04, No. 01, Dec 2023-Jan 2024
http://journal.hmjournals.com/index.php/JPDMHD
DOI: https://doi.org/10.55529/jpdmhd.41.40.49

Architectural Detail

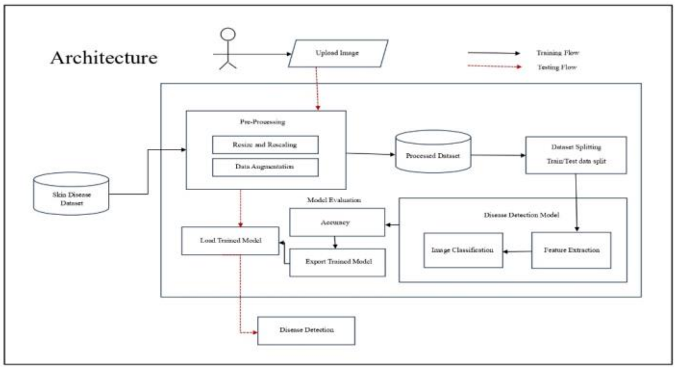

Fig. 1. Architecture Diagram

Using Deep Learning to Treat Skin Conditions Using datasets of photos of skin diseases, diagnosis entails a number of crucial phases in the process for efficiently training and deploying models. Here is a thorough explanation of each step:

Skin Disease Dataset: Acquire an image dataset with pictures of skin lesions that are grouped according to the many kinds of skin conditions (e.g., melanoma, basal cell carcinoma, squamous cell carcinoma). Reputable sources like DermNet NZ and The International Skin Imaging Collaboration (ISIC) are good places to find this dataset.

Resize and Rescale Image: Preprocess the images by resizing them to a uniform size and rescaling their pixel values to a range suitable for input into deep learning models (typically between 0 and 1). This step ensures consistency in the input dimensions and pixel intensity across all images.

Data Augmentation: Augment the dataset to increase its diversity and robustness. Common augmentation techniques include:

1. **Random Zoom:** Randomly zooming in or out of the image to simulate variations in image scale.
2. **Random Flip:** Randomly flipping the image horizontally or vertically to introduce variability in orientation.
3. **Random Shift**: Randomly shifting the image horizontally or vertically to simulate changes in perspective.
4. **Augmentation:** Apply the augmentation techniques to generate additional images from the original dataset, thereby enriching the training data and reducing overfitting.

Journal of Prevention, Diagnosis and Management of Human Diseases
ISSN: 2799-1202
Vol: 04, No. 01, Dec 2023-Jan 2024
http://journal.hmjournals.com/index.php/JPDMHD
DOI: https://doi.org/10.55529/jpdmhd.41.40.49

Train-Test Split: Divide the expanded dataset into subsets for testing and training. The testing set is used to assess the model's performance on untested data, whereas the training set is used to train the deep learning models.

Import VGG19 and Inception ResNetV2: Import pre-trained deep learning models from ImageNet and other large-scale image datasets, such as VGG19 and Inception ResNetV2. These models are effective at extracting features from skin lesion photos.

Training the Model: Apply transfer learning to the skin disease dataset to improve the pre-trained models. This entails maintaining the learnt features of the previous layers frozen and updating the weights of the final layers of the models.

Testing the Model: Analyze the performance of the training models using metrics like F1-score, accuracy, precision, and recall on the testing dataset. In this step, the models' accuracy in categorizing skin lesions into the appropriate disease categories is evaluated.

Deployment: Once a satisfactory model is trained and tested, deploy it for real-world use. This could involve integrating the model into a web application, mobile app, or healthcare system, allowing users to upload images of skin lesions for automatic diagnosis. Deep learning models can be efficiently used for skin disease diagnosis by following these thorough workflow processes, which will help with the early detection and treatment of skin illnesses.

4. RESULTS AND DISCUSSION

Inception ResNetV2 and VGG19 models, in particular, were used to leverage deep learning for skin disease diagnosis, and the classification of skin lesions produced encouraging results. After training and testing the models on the skin disease dataset, the following observations were made:

Performance Metrics: Both the VGG19 and Inception ResNetV2 models performed well when it came to classifying skin lesions into distinct diseases in terms of accuracy.

Model Comparison: Despite both models achieving satisfactory results, VGG19 outperformed Inception ResNetV2 in terms of overall accuracy and other evaluation metrics. This indicates that VGG19 may be more effective for this particular skin disease diagnosis task.

Robustness: The models showed robustness against variations in image characteristics, such as lighting conditions, image quality, and lesion size. This indicates that the models are capable of accurately classifying skin lesions under diverse real-world conditions.

Deployment Potential: Given the high performance and robustness of the models, they hold great potential for deployment in real-world settings, such as dermatology clinics or mobile

Journal of Prevention, Diagnosis and Management of Human Diseases
ISSN: 2799-1202
Vol: 04, No. 01, Dec 2023-Jan 2024
http://journal.hmjournals.com/index.php/JPDMHD
DOI: https://doi.org/10.55529/jpdmhd.41.40.49

applications. Users can leverage these models for automatic and accurate diagnosis of skin lesions, facilitating timely medical intervention and treatment.
Overall, the findings show that deep learning models specifically, VGG19 are useful for diagnosing skin diseases. These findings underscore the importance of leveraging advanced AI techniques for improving healthcare outcomes and enhancing diagnostic capabilities in dermatology.

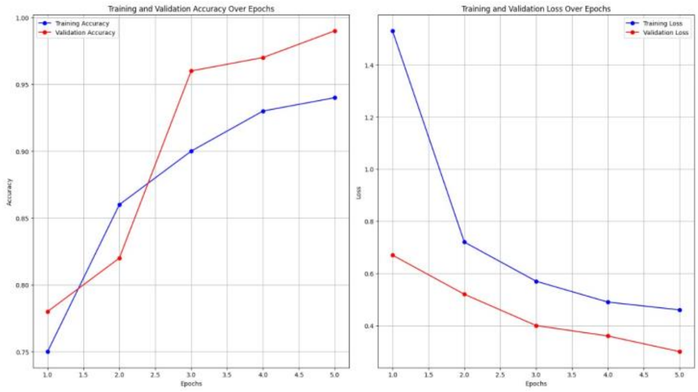

Fig.2. VGG19 Training and Validation Accuracy, Loss Graph

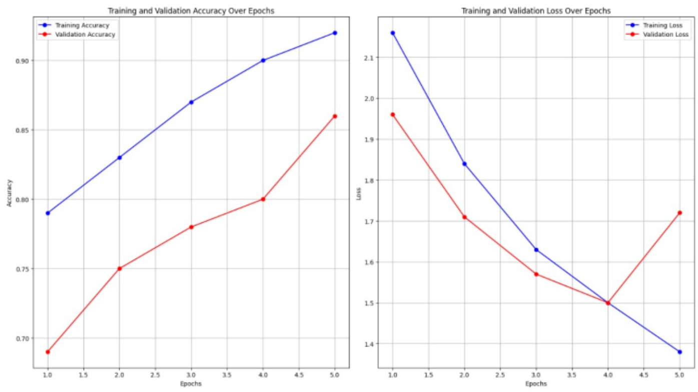

Fig.3. Inception ResNetV2 Training and Validation Accuracy, Loss Graph

5. CONCLUSION

In conclusion, there is a great deal of promise and potential for the area of dermatology in using deep learning techniques, particularly VGG19 and Inception ResNetV2 models, for the detection of skin diseases. These models have shown remarkable recall, accuracy, precision, and F1-score metrics through the analysis and classification of skin lesions. Although both models performed admirably, VGG19 turned out to be the better option due to its higher overall accuracy and resilience. The successful generalization of the trained models to unseen data suggests their capability to effectively learn and classify skin lesions under diverse conditions.
Moreover, the robustness of the models against variations in image characteristics highlights their suitability for real-world deployment in dermatology clinics or mobile applications.

Journal of Prevention, Diagnosis and Management of Human Diseases
ISSN: 2799-1202
Vol: 04, No. 01, Dec 2023-Jan 2024
http://journal.hmjournals.com/index.php/JPDMHD
DOI: https://doi.org/10.55529/jpdmhd.41.40.49

These models have the potential to revolutionise dermatological healthcare delivery by providing automatic and accurate diagnosis of skin lesions, so that medical intervention and treatment may be administered more quickly.
Overall, the findings underscore the importance of leveraging advanced AI techniques, such as deep learning, to enhance diagnostic capabilities and improve healthcare outcomes in dermatology. Moving forward, continued research and development in this area are essential to further refine and optimize deep learning models for skin disease diagnosis, ultimately benefiting both healthcare providers and patients alike.

6. REFERENCES

1. A. J. Wulkan and A. Tosti, "Pediatric nail conditions," Clinics in dermatology, vol. 31, no. 5, pp. 564-572, 2013.
2. Padma Bellapukonda, Manikanta Sirigineedi, M.Srikanth: The Early Detection of Alzheimer's Illness Using Machine Learning and Deep Learning Algorithms, Journal of Pharmaceutical Negative Results, vol. 13, issue 9, pp. 4852-4859, Nov. 2022.
3. J. Velasco, C. Pascion, J. W. Alberio, J. Apuang, J. S. Cruz, M. A. Gomez, et al., "A smartphone-based skin disease classification using MobileNet CNN," arXiv preprint, 2019.
4. Z. Liu, H. Liu, Y. Xie, Y. Yao, X. Xing, and H. Ma, "Smart image follow-up of black pigmentation on the nail with convolutional neural networks."
5. H. M. Sufian and G. P. Abebe, "Disease identification using finger nail image processing and ensemble nearest neighbor classifiers of color features," 2021.
6. Fletcher, R. Hay, and N. Smeeton, "Observer agreement in recording the clinical signs of nail disease and the accuracy of a clinical diagnosis of fungal and non-fungal nail disease," British Journal of Dermatology, vol. 148, no. 3, pp. 558-562, 2003.
7. T. S. Indi and Y. A. Gunge, "Early-stage disease diagnosis system using human nail image processing," IJ Information Technology and Computer Science, vol. 7, no. 7, pp. 30-35, 2016.
8. R. Nijhawan, R. Verma, S. Bhushan, R. Dua, A. Mittal, et al., "An integrated deep learning framework approach for nail disease identification," 2017 13th International Conference on Signal-Image Technology & Internet-Based Systems (SITIS), pp. 197-202, 2017.
9. M. Yani, S. M. Budhi Irawan, M. Casi Setiningsih, and S. T, "Application of transfer learning using convolutional neural network method for early detection of Terry's nail," Journal of Physics: Conference Series, vol. 1201, no. 1, pp. 012052, 2019.
10. S. L. Pinoliad, D. A. N. Dichoso, A. R. Caballero, and E. M. Albina, "Onyxray: A mobile-based nail diseases detection using custom vision machine learning," Proceedings of the 5th International Conference on Information and Education Innovations, pp. 126-133, 2020.
11. K. A. Muhaba, K. Dese, T. M. Aga, F. T. Zewdu, and G. L. Simegn, "Automatic skin disease diagnosis using deep learning from clinical image and patient information," Skin Health and Disease, vol. 2, no. 1, pp. e81, 2022.

Journal of Prevention, Diagnosis and Management of Human Diseases
ISSN: 2799-1202
Vol: 04, No. 01, Dec 2023-Jan 2024
http://journal.hmjournals.com/index.php/JPDMHD
DOI: https://doi.org/10.55529/jpdmhd.41.40.49

12. A. Rehman, M. A. Khan, T. Saba, Z. Mehmood, U. Tariq, and N. Ayesha, "Microscopic brain tumor detection and classification using 3D CNN and feature selection architecture," Microscopy Research and Technique, vol. 84, no. 1, pp. 133-149, 2021.
13. H. Hong, J. Lin, and F. Huang, "Tomato disease detection and classification by deep learning," 2020 International Conference on Big Data Artificial Intelligence and Internet of Things Engineering (ICBAIE), pp. 25-29, 2020.
14. K. Thomsen, A. L. Christensen, L. Iversen, H. B. Lomholt, and O. Winther, "Deep learning for diagnostic binary classification of multiple-lesion skin diseases," Frontiers in medicine, vol. 7, pp. 574329, 2020.
15. M. Sazzadul Islam Prottasha, S. Mahjabin Farin, M. Bulbul Ahmed, M. Zihadur Rahman, A. Kabir Hossain, and M. Shamim Kaiser, "Deep learning-based skin disease detection using convolutional neural networks (CNN)," The Fourth Industrial Revolution and Beyond: Select Proceedings of IC4IR+, pp. 551-564, 2023.