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Skin Cancer Classification using SkinNet

Kiruthika T, Kaviya G, Jeslin Shanthamalar J, Nithya S, and Mercy Paul Selvan

Department of Computer Science and Engineering, Sathyabama Institute of Science and Technology, Chennai, India

ABSTRACT
Addressing the critical health problem of skin cancer, rapid and precise lesion detection is imperative for powerful treatment. The model concentrates on identifying seven specific skin most cancers types: Melanoma, Basal cell carcinoma, Benign keratosis-like lesions, Dermato-fibrosarcoma protuberans, Actinic keratosis, Melanocytic nevi, and Vascular lesions. The proposed model, SkinNet is a specialized model designed to enhance an accurate classification of lesions and skin cancer diseases. The implementation of SkinNet achieved an accuracy rate of 98%, marking a significant advancement in healthcare with promising implications for both healthcare providers and patients in the future.

KEYWORDS
Machine Learning, Deep Learning, Lesion Classification, Convolutional Neural Network.

1. INTRODUCTION

Functioning as the body's biggest organ, the skin serves a various variety of roles as the primary defense mechanism. It acts as a shield, safeguarding internal organs from external factors, while also regulating body temperature and providing robust protection against the skin disease. Comprising 3 layers—epidermis, dermis, and hypodermis—the skin performs a critical position in maintaining average properly-being. Despite its complexity, concerns about skin most cancers often emerge. Skin most cancers originates from abnormal skin cell proliferation, initially providing as ance, which can appear in benign or malignant forms. Malignant ance disrupts natural bodily processes and has the capability to unfold to other regions, posing enormous health risks.

Apart from indoor environments, increasing concerns stem from increased air pollution, which creates a favorable environment for skin disease, especially skin cancer. Skin cancers classification using deep learning [10] knowledge of strategies has emerged as a pivotal area in clinical photograph analysis. In the area of deep neural networks, excellent advancements were made in growing computerized architectures talented in appropriately discerning diverse skin lesions. This innovative technique ambitions to enhance early prediction, analysis, and classification of skin cancer, addressing the critical need for well-timed intervention as a way to enhance affected person consequences. Leveraging the power of deep learning algorithms, those systems examine dermatoscopic images, paving the way for more efficient and precise skin most cancers type, thereby helping healthcare professionals of their diagnostic techniques.

The powerful subset of artificial intelligence is deep learning, that provides precise tools for image segmentation, and reveals the complex neural networks of the human brain. The research goal types revolve around quick and effective ways to detect skin cancer, emphasizing the critical importance of what has been lost.

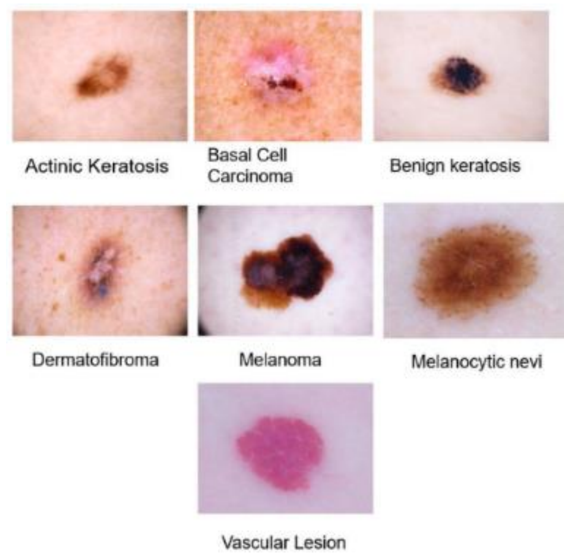

Fig. 1 Types of Skin Diseases

2. RELATED WORK

In a previous study [1], a refined version of the ISIC dataset was employed. Within this dataset, dermatofibroma and nevus pigmentosus constitute benign tumors, while squamous cell carcinoma and cancer are labeled as skin cancers. To heighten precision, predictions had been carried out on a set of 2072 lesions encompassing both benign and malignant nonpigmentation lesions [2]. This exhaustive and current cancer data imparts valuable insights for researchers, clinicians, and policymakers. The initiative stands as a pivotal model for comprehending cancer type prevalence and trends, furnishing an essential foundation for formulating strategies [3] in cancer prevention, diagnosis, and treatment.

The inclusion of two different deep learning methods in the ResNet-101 model, [4] resulting in a multidimensional approach to skin cancer detection. The functionality of CNN-based totally approaches to transform into progressive diagnostic tools (DBs). To enhance the clinical applicability of the outcomes, [12] it's far encouraged those future comparative studies be performed in more realistic situations, making use of external Out-of-Distribution (OOD) take a look at units that represent a numerous range of ethnicities and scientific occurrences of cancer subtypes.

Unlike many traditional models that rely on complex extraction and preprocessing steps, [13] Kulkarni's CNN was designed to directly accept pixel data and disease labels as input. This approach offers a truthful and green technique to categorizing pores and skin lesions. Mixing pixel-level information and relevant disease labels in the training pipeline facilitates model understanding of skin conditions, increasing classification accuracy. The method concerned [14] making use of deep studying strategies and ensemble stacking of device studying fashions.

Skin cancers detection results were correctly attained by leveraging a single, exceptionally lightweight deep learning model [15]. This model's versatility and practical applicability in real-world were demonstrated through its integration into a mobile app. The assessment included the testing of various neural network models, consisting of DenseNet201, MobileNetV2, ResNet50V2, ResNet152V2, Xception, VGG16, VGG19, and Google Net [16], with their overall performance evaluated on graphical processing units (GPUs).

Introducing an automatic cancer classifier leveraging a deep convolutional neural network (DCNN) architecture [17] is crafted together, incorporating multiple layers to extract features from lesions and skin images, ranging from low to excessive-level, in a distinctive manner. The focal point is on automated retinal picture quality [18] evaluation for computer-aided analysis.

The system employs energy functions based on the Non-Subsampled Shearlet Transform (NSST) [20], coupled with a Support Vector Machine (SVM) classifier. Ensemble learning [21] models are used to categorize the skin cancers, enhancing the general classification technique.

3. PROPOSED SYSTEM

In the research, the initial step involves data collection which is the HAM10000 dataset [5] [6]. To classify the cancers, the SkinNet model is introduced in our research to achieve more accuracy in predicting the types skin cancer [10] disease. A sequential model from Keras library is used which will help to make the implementation of neural networks in an easy way. The system is designed to identify skin cancers in its early phases, covering the initial and intermediate stages across numerous forms of the disorder. Its predictive potential extends to detecting lesions characteristic of early cancer, basal cellular carcinoma, benign keratosis-like lesions, dermatofibrosarcoma protuberans, actinic keratosis, melanocytic nevi, and vascular lesions.

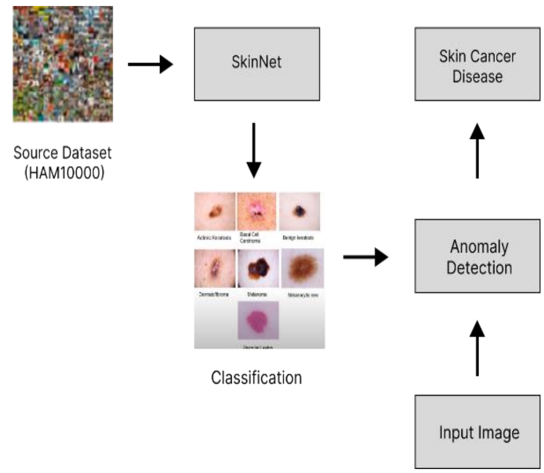

Fig. 2 Architecture Diagram for Proposed Model

3.1 Architecture Diagram:

Figure 2 represents the HAM10000 dataset, the integrated framework employs a model for classifying 7 skin cancer types. By seamlessly integrating anomaly detection, the system finds out the abnormal patterns, thereby improving its ability to detect potential malignancies at an early stage. This approach carries predictive factors to predict elements to anticipate the emergence of distinct skin cancers diseases. The complete system provides an answer, combining precise classification, anomaly detection, and proactive identification of developing skin conditions.

4. MODEL TRAINING

4.1. Dataset:

In the proposed approach, the idea is to use the resources available inside the “HAM10000” from Kaggle to train and test our mode. The image is in RGB scale with 28x28 pixels. The dataset consists of 10000 images with the seven types of skin cancer disease which is used to train and test our model.

4.2. SkinNet Model:

Figure 3 represent the types of skin cancer is classified into classes which is known as labels. By using such a diverse dataset, the aim is to enable the proposed model is to recognize the skin conditions, enhancing its capacity to predict and classify various skin cancers kinds.

Label	Images
4	6705
6	1113
2	1099
1	514
0	327
5	142
3	115

Fig. 3 Labels of Cancer Types

Table. 1 Layers of SkinNet Model

Layers	Output Size	Parameter
Input Image	28, 28, 3	0
Convolution	28, 28, 32	896
Max Pooling	14, 14, 32	0
Batch Normalization	14, 14, 64	128
Convolution	14, 14, 64	18496
Convolution	14, 14, 64	36928
Max Pooling	7, 7, 64	0
Batch Normalization	7, 7, 64	256
Convolution	7, 7, 128	73856
Convolution	7, 7, 128	147584
Max Pooling	3, 3, 128	0
Batch Normalization	3, 3, 128	512
Convolution	3, 3, 256	295168
Convolution	3, 3, 256	590080
Max Pooling	1, 1, 256	0
Flatten	256	0
Dropout	256	0
Dense	256	65792
Batch Normalization	256	1024
Dense	128	32896
Batch Normalization	128	512
Dense	64	8256
Batch Normalization	64	256
Dense	32	2080
Batch Normalization	32	128
Dense	7	231
Output	7	0

The RandomOverSampler method proves useful in addressing imbalanced datasets by means of using oversampling strategies. Specifically, the 'fit_resample' method rebalances elegance distribution by means of growing synthetic samples for the minority magnificence. This model procedures a 28x28 image size with RGB image the usage of convolution, pooling, and absolutely related layers. It includes 231 trainable parameters and is going via spatial size reduction, feature extraction, and normalization are expecting output lessons. The model is being used to define a dictionary, mapping numeric labels to skin lesion types with shorthand codes and descriptive labels.

The model uses train_test_split from sklearn.Model_selection to break up Data and Label into training and testing sets (75% training, 25% testing). The random_state parameter guarantees reproducibility. The sample images of the dataset are in Fig. 4. Then, the to_categorical function from keras.utils, then uses it to convert express labels in each education and take a look at units (y_train and y_test) to one-hot encoded format, making sure uniformity in label layout for neural network models.

The Datagen processes education facts by means of normalizing image values to the range zero to one, rotating images up to 10%, zooming in with the aid of 10%, and randomly shifting horizontally and vertically through up to 10%.

Fig. 4 Sample Images

The testgen simplifies checking out and validation, rescaling pixel values to a number 0 to one (rescale= (1. /255)). The TensorFlow's imports Adam and Adamax optimizers, vital for adjusting neural network weights during education to limit prediction errors. Importing the ReduceLROnPlateau from Keras library, the reduction callback in Keras, which adjusts the gaining knowledge at some stage in education based totally at the validation accuracy. If there may be no development in accuracy for two epochs, it reduces the learning rate by half, with a minimal limit of 0.00001.

Then, the model structure is created by adding 26 layers with different parameters is trained the SkinNet model. This indicates that there are extra layers than one [1]. The neural network model the usage of training facts (X_train, y_train) with 25 epochs, a batch length of 128, and validation information (X_test, y_test). The model incorporates the ReduceLROnPlateau callback for adaptive learning charge adjustment for the duration of education.

The hardware and software used to develop the model were:

RAM :16 GB
GPU : Intel Iris Xe
Processor : Intel Core i5
OS : Microsoft Windows 10

Following model training with various parameters, the model is built within the Jupyter Notebook—an open-source distribution tailored for scientific computing the usage of Python and other programming languages. Application deployment is facilitated by Flask, a web framework offering important tools and libraries, which includes NumPy, pandas, os, matplotlib, seaborn, shutil, TensorFlow, PIL, and Keras. Matplotlib and Seaborn play key roles in image operations and plotting, even as shutil and os control path and directory operations on documents. Model building includes seaborn, scikit-study, and sklearn for responsibilities like class reviews, ROC curves, and confusion matrices. The extensively applied NumPy and pandas libraries manage array processing and statistics analysis. The deployment of application building encompasses diverse technology, empowering developers to create dynamic web packages.

5. DISCUSSION OF RESULT

In this research, the training dataset 75% of the images and the testing dataset with the remaining 25% are applied for the SkinNet model. The dataset encompasses 7 distinct classes, namely Melanoma, Basal cell carcinoma, Squamous cell carcinoma, Dermatofibroma, Actinic Keratosis, Benign keratosis lesions, and Vascular lesions. The SkinNet model demonstrates an accuracy of 98% in classifying the skin cancers.

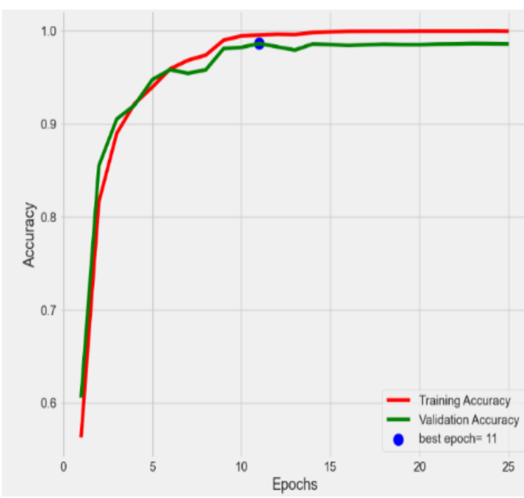

Fig. 5 Model Accuracy

In Fig. 5, the validation accuracy of skin most cancers types is depicted, showcasing the effects of Convolutional Neural Networks (CNN) implementation. This comprehensive technique is designed to both train and determine the version's efficacy in classifying various skin conditions. The graph illustrates the education and validation loss in the skin lesion class, leveraging the capabilities of a CNN.

Fig. 6 illustrates the validation loss, which serves as a critical metric for assessing the performance of the convolutional neural community (CNN). This metric presents a visible illustration of the CNN's accuracy in distinguishing between diverse kinds of lesions and pores and skin cancers. By analyzing the validation loss depicted in the discern, researchers and practitioners benefit precious insights into the version's efficacy and its potential to successfully classify extraordinary types of pores and skin abnormalities. The validation loss curve offers a dynamic depiction of the model's gaining knowledge of manner, showcasing fluctuations in performance over the path of education and validation epochs. This data is instrumental in excellent-tuning the CNN architecture and optimizing its overall performance for correct lesion category.

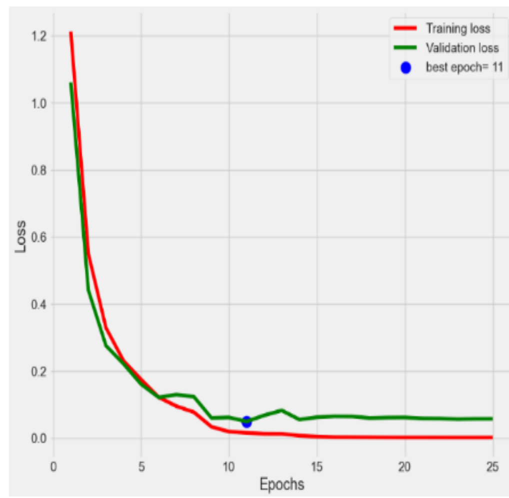

Fig. 6 Model Loss

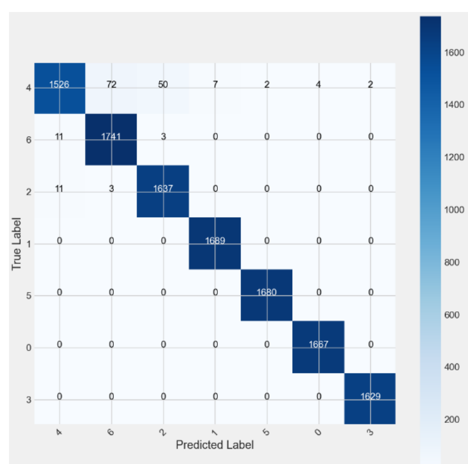

Fig. 7 Confusion Matrix

In the context of skin cancer diagnosis, Fig. 7 provides a complete matrix that details the version's predictions for various skin most cancers sorts. This matrix now not handiest showcases the model's detection competencies but also compares those predictions with the real classifications of the lesions. By offering this records, Fig. 7 serves as a important device for comparing the accuracy and reliability of the model in distinguishing among specific pores and skin most cancers categories, thereby supplying valuable insights into its overall performance and capability areas for improvement.

Table. 2 Output of SkinNet Model

Input	Detection	Original Name
	Actinic Keratoses	Actinic Keratoses
	Basal cell Carcinoma	Basal cell Carcinoma
	Melanocytic nevi	Benign keratosis-like lesions
	Dermatofibroma	Dermatofibroma
	Melanocytic nevi	Dermatofibroma
	Melanocytic nevi	Melanocytic nevi
	Melanoma	Melanoma
	Benign keratosis-like lesions	Vascular lesions
	Basal cell carcinoma	Benign keratosis-like lesions
	Benign keratosis-like lesions	Benign keratosis-like lesions

6. COMPARATIVE ANALYSIS

The comparative analysis of the previous paper is done in our research to enhance our SkinNet model. L. Yu's proposed approach, the depth contributes to richer feature extraction, it also introduces increased complexity and computational cost. H. K. Kondaveeti paper's dataset, the class distribution is uneven, potentially leading to biased model performance, specifically for minority training.

R Raja Subramanian paper mentions implementing a multiple models and methodologies but gives result for only a subset of them. X. Wang research paper does not extensively discuss the real-world deployment issues, consisting of the interpretability of the model's choices and the potential challenges in integrating the proposed approach into scientific workflows. A. Javaid paper introduces a novel wrapper-based feature selection approach but lacks a complete exploration and comparison with alternative techniques. A more in-depth evaluation of various algorithms for feature selection is important to recognize their various influences on classification performance.

Table. 3 Comparison with other works

No	Researcher	Algorithms	Accuracy
1	L. Yu (2017)	FCRN	94.90%
2	H. K. Kondaveeti (2020)	ResNet50	90.00%
3	R. Raja Subramanian (2021)	CNN	>80.00%
4	X. Wang (2021)	ResNet101 and DenseNET121	87.33%
5	A. Javaid (2021)	Random Forest	93.89%
6	Proposed Work	SkinNet	98.00%

7. CONCLUSION WITH FUTURE WORK

The development of this project accomplished a big fulfillment of enhancing the performance of the web application for recognizing and knowledge images. Specifically, the program now efficiently identifies images with an impressive accuracy of 98%. This success is a result of the efforts to enhance the program's abilities using numerous sets of images and making it smarter in recognizing distinct patterns. Additionally, this system has been made more powerful by way of using numerous datasets, which means that it could handle a much broader range of images and situations. The way the images are put together for evaluation has also been progressed, making the program even higher at understanding and deciphering the visible facts.

The implementation of SkinNet indicates a full-size development in healthcare generation, supplying promising implications for healthcare carriers and sufferers alike. This studies underscores the significance of leveraging device studying strategies in dermatology for improved patient consequences and underscores the ability for in addition improvements in pores and skin cancer diagnosis and remedy.

In moving forward, key steps for project development include expanding the dataset, fine-tuning hyperparameters, exploring ensemble learning and transfer learning, and incorporating interpretability. Real-time deployment and continuous monitoring, along with a user-friendly interface for healthcare professionals, are critical for practical application. These measures collectively aim to evolve the project into an effective tool for skin cancer diagnosis, advancing medical imaging and healthcare technology.

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AUTHORS

Kiruthika T is currently pursuing her B.E. degree in Computer Science and Engineering from Sathyabama Institute of Science and Technology, Chennai. Her areas of interests are Data Science, Artificial Intelligence and Machine Learning.

Corresponding Author Email: kiruthikathangapandiyan@gmail.com

Kaviya G is currently pursuing her B.E. degree in Computer Science and Engineering from Sathyabama Institute of Science and Technology, Chennai. Her areas of interests are Distributed Systems, Cloud Computing, System Security and Machine Learning.

Email: imkaviyag@gmail.com

J Jeslin Shanthamalar is currently working as Assistant Professor in the Department of Computer Scienc and Engineering, Sathyabama Institute of Science and Technology, Chennai. She completed her Ph.D. programme in the Department of Information Science and Technology, Anna University, Chennai, India, as a full-time scholar. She has more than 10 years of experience in Teaching, Research and Industry. Her areas of specialization include Data Mining, Image Processing, Machine Learning, Deep Learning and Medical Image Analysis. She has published more than 10 papers in reputed journals, patents and conferences.

Email: jeslin.cse@sathyabama.ac.in

S Nithya, working as Assistant professor in the Department of Computer Science and Engineering, Sathyabama Institute of Science and Technology, Chennai. She is pursuing her research in the Machine Learning and Deep Learning domain. She has more than 4 years of experience in Teaching, Research and Industry. She has published a few patents and papers in conferences and journals.

Email: nithya.cse@sathyabama.ac.in

Mercy Paul Selvan, working as Professor in the Department of Computer Science and Engineering, Sathyabama Institute of Science and Technology, Chennai. She pursued her M.E. and Ph. D. in Computer Science and Engineering. She is pursuing her research in the Artificial Intelligence, Data Science and Natural Language Processing domain. She has more than 15 years of experience in Teaching, Research and Industry. She has published more than 50 papers in reputed journals, and conferences.

Email: mercypaulselvan.cse@sathyabama.ac.in