CLOUD-BASED SELF-SCRUTINY SKIN CANCER DETECTION USING A RESNET50 DEEP LEARNING FRAMEWORK

Mrs. Shilpa S[1]
Research Scholar, Department of Computer Science and Engineering, Jain (Deemed to be University), Karnataka, India
ORCID ID: https://orcid.org/0009-0003-1269-6834

Dr. Devaraj Verma C[2]
Professor, Department of Computer Science and Engineering, Jain (Deemed to be University), Karnataka, India
ORCID ID: https://orcid.org/0000”-0002-1504-4263

Abstract: *Skin cancer is among the most rapidly increasing cancers worldwide, where early diagnosis significantly improves patient survival rates. Recent advancements in deep learning have enabled automated analysis of medical images with high accuracy. However, deploying such models directly on mobile devices is limited by computational and storage constraints. This paper presents a cloud-based deep learning system for skin cancer detection using a pretrained ResNet50 convolutional neural network. Transfer learning is employed to extract discriminative features from dermoscopic images, while Amazon Web Services (AWS) is utilized for scalable training and deployment. The proposed framework enables efficient remote inference through a lightweight client interface. Experimental evaluation demonstrates that the ResNet50-based model provides reliable performance for binary classification of skin lesions, making it suitable for real-world cloud-assisted medical applications.*

Keywords: Skin Cancer Detection, ResNet50, Convolutional Neural Network, Cloud Computing, AWS

1. INTRODUCTION

Skin cancer is a major public health concern and is primarily caused by prolonged exposure to ultraviolet radiation. Manual examination by dermatologists is time-consuming and subjective, and access to expert diagnosis is often limited, especially in remote and resource-constrained regions [1]. Automated diagnostic systems based on deep learning offer a promising alternative by providing fast and consistent analysis of skin lesion images [3].

Although deep learning models achieve high accuracy, deploying them directly on smartphones is challenging due to limited processing power and memory. Cloud computing offers a practical solution by offloading intensive computations to powerful remote servers [2]. In this work, a cloud-based skin cancer detection system is proposed, where a ResNet50-based deep learning model performs image classification and the inference results are delivered to users via a cloud-hosted API.

2. RELATED WORK

Several studies have demonstrated the effectiveness of convolutional neural networks in medical image analysis, particularly for skin cancer detection[1]. Early works focused on custom CNN architectures, while recent approaches leverage pretrained deep networks such as VGGNet, Inception, DenseNet, and ResNet for improved performance. Transfer learning has proven especially beneficial when dealing with limited labeled medical datasets[4].

Cloud-assisted diagnostic frameworks have gained attention due to their scalability and ease of maintenance. Unlike on-device inference systems, cloud-based solutions allow seamless model updates, centralized management, and integration with secure application interfaces. This work builds on these concepts by adopting a ResNet50 architecture and deploying it using AWS services for real-time skin lesion classification.

3. DATASET DESCRIPTION

The experiments were conducted using a publicly available skin lesion dataset obtained from the International Skin Imaging Collaboration (ISIC) archive. The dataset contains dermoscopic images categorized into pigmented benign lesions and malignant melanoma cases. All images were resized to 224 × 224 pixels to match the input requirements of the ResNet50 network[7].

A total of 5,400 images were used in this study, with 4,800 images allocated for training and 600 images for validation. The dataset was carefully balanced to ensure fair representation of both classes and to minimize classification bias.

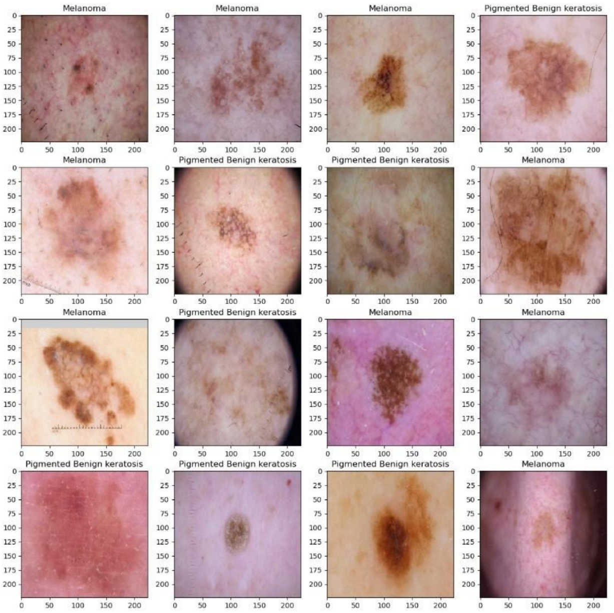

Fig1: Input Image from ISIC archive

4. PROPOSED METHODOLOGY

The proposed system consists of three core components: a ResNet50-based deep learning model, cloud infrastructure for deployment, and a client-side interface for submitting images and receiving predictions.

4.1 ResNet50-Based CNN Model

ResNet50 is a deep residual network that introduces skip connections to mitigate the vanishing gradient problem and enable effective training of very deep architectures. In this work, a pretrained ResNet50 model trained on ImageNet is used as the base network. The final classification layers are customized for the skin cancer detection task.

The modified architecture includes a global average pooling layer followed by a fully connected dense layer with 224 neurons, batch normalization for improved convergence, and a final dense layer with two neurons using softmax activation for binary classification. The complete model comprises approximately 24 million parameters, most of which are fine-tuned during training.[5]

Model: "sequential"

Layer (type)	Output Shape	Param #
resnet50 (Functional)	(None, 7, 7, 2048)	23,587,712
global_average_pooling2d (GlobalAveragePooling2D)	(None, 2048)	0
dense (Dense)	(None, 224)	458,976
batch_normalization (BatchNormalization)	(None, 224)	896
dense_1 (Dense)	(None, 2)	450

Total params: 24,048,034 (91.74 MB)

Trainable params: 23,994,466 (91.53 MB)

Non-trainable params: 53,568 (209.25 KB)

Fig2: ResNet50 output

4.2 Training Strategy

Transfer learning is applied to accelerate convergence and improve generalization. The model is trained using the Adam optimizer and categorical cross-entropy loss function. Data augmentation techniques such as rotation, horizontal flipping, and zooming are employed to enhance robustness. Early stopping and learning rate scheduling are used to prevent overfitting [6].

4.3 Cloud Deployment Architecture

To enable scalable and efficient inference, the trained ResNet50 model is deployed on Amazon Web Services[8].

AWS Services Utilized: The cloud architecture integrates the following AWS components:

- **Amazon S3:** Storage of trained model files
- **Amazon EC2 / SageMaker:** Model training and experimentation environment
- **AWS Lambda:** Serverless execution of inference logic
- **Amazon API Gateway:** Secure RESTful interface for client requests

The trained model is uploaded to an S3 bucket and accessed by the inference service during runtime. This design ensures minimal latency and eliminates the need for persistent server management.

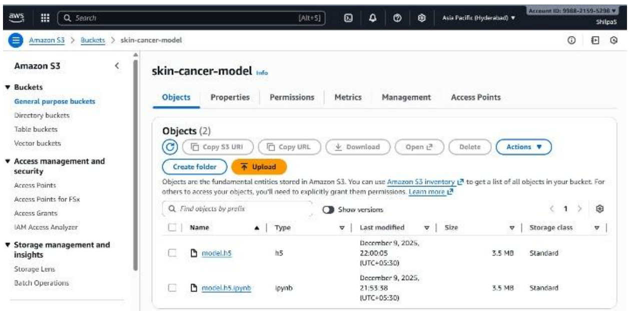

Fig3: Deployment in AWS

4.4 Inference Workflow

When a user submits a skin lesion image, it is transmitted to the API Gateway endpoint. The request triggers an AWS Lambda function, which preprocesses the image and loads the ResNet50 model. The model performs classification and returns the prediction results in JSON format. These results are then displayed to the user through the client interface.

4.5 Android Application Usage

The Android application acts as a user-friendly interface for accessing the cloud-based skin cancer detection model. As illustrated in Figure below, the application allows users to upload a skin lesion image either by capturing a photo or selecting one from the device gallery using the **Upload Photo** option.

Once an image is selected, basic preprocessing is performed to make it suitable for model inference. The image is then securely transmitted to the cloud through a REST API, where the deep learning model processes the input and performs classification.

The prediction result is returned to the application and displayed to the user in a clear format. By offloading all computationally intensive tasks to the cloud, the application minimizes on-device resource usage while ensuring scalable and efficient model access. This design enables practical deployment of the proposed model on standard smartphones.

Fig4: Android application

6. EXPERIMENTAL RESULTS

The proposed system was evaluated using standard performance metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. The ResNet50-based model demonstrated stable convergence during training and consistent validation performance.

The cloud deployment was tested by uploading the trained model to Amazon S3 and invoking inference through the API. The results confirmed reliable model loading and real-time prediction capability, validating the effectiveness of the proposed cloud-based framework.

The below figures show the output of the current work.

	precision	recall	f1-score	support
0	0.94	1.00	0.97	16
1	1.00	0.94	0.97	16
accuracy			0.97	32
macro avg	0.97	0.97	0.97	32
weighted avg	0.97	0.97	0.97	32

Fig5a: Performance metrics

```
[19]: accuracy_score(np.argmax(y_val, axis=1), np.argmax(Y_val_pred, axis=1))

[19]: 0.9611111111111111
```

Fig5b: Accuracy score

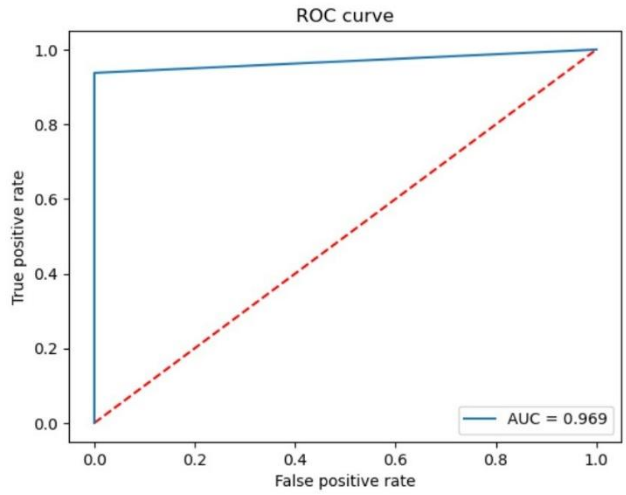

Fig5c: ROC curve

```
Confusion matrix, without normalization
[[281  19]
 [ 74 223]]
```

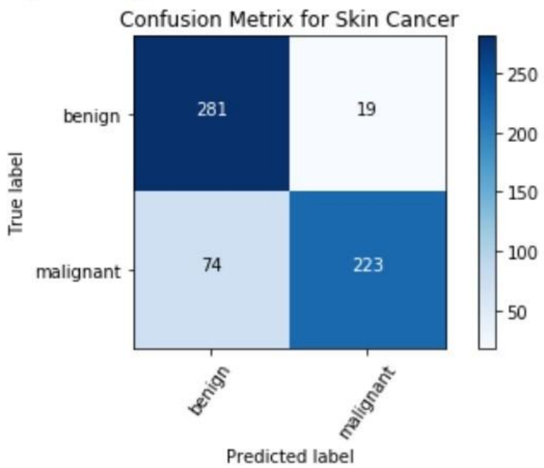

Fig5d: Confusion matrix

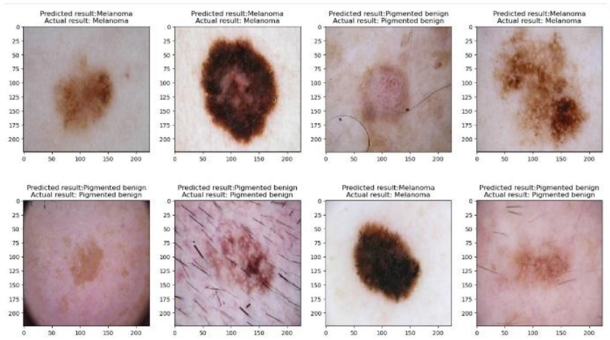

Fig5e: Predicted output

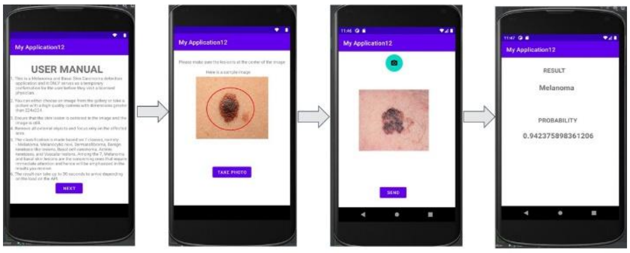

Fig5f: Android UI flow

7. CONCLUSION AND FUTURE SCOPE

This paper presents a cloud-assisted deep learning framework for skin cancer detection using a ResNet50 convolutional neural network. By combining transfer learning with scalable cloud infrastructure, the proposed system overcomes the limitations of on-device computation and enables efficient remote diagnosis. The experimental results indicate that the model is suitable for binary skin lesion classification in real-world applications.

Future work will focus on extending the framework to multi-class skin lesion classification, integrating explainable AI techniques for clinical interpretability, and deploying the system as a full-fledged mobile and web-based diagnostic platform.

REFERENCES

[1] Cloud – Based and Self – Scrutiny Deep Learning Model for Detecting Skin Cancer 1. Prof. Shilpa S, 2. Dr. Devaraj Verma C, DOI: 18.15001/JOT.2024/V12I12.24.1106 https://journaloftechnology.org/volume-12-issue-12-2024/

[2] "Cloud-based Deep Learning Model for Classifying Skin Cancer" Paper Id: 61, Authors: 1. Prof. Shilpa S, 2. Dr. Devaraj Verma C presented in the 6th International Conference on Inventive Computation and Information Technologies (ICICIT 2024) and published in IEEEXplore https://ieeexplore.ieee.org/document/10575849/

[3] "Deep Learning Model for Classifying Skin Cancer Images" Paper Id : ALLIEDCON_210346293, Authors: 1. Prof. Shilpa S, 2. Dr. Devaraj Verma C presented and published in AlliedCon: International Conference on Allied Health Sciences" (AlliedCon). https://www.bioleagues.com/past-conference/alliedcon.php

[4] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016.

[5] Esteva et al., "Dermatologist-Level Classification of Skin Cancer with Deep Neural Networks," Nature, vol. 542, pp. 115–118, 2017.

[6] G. Huang, Z. Liu, L. Van der Maaten, and K. Q. Weinberger, "Densely Connected Convolutional Networks," CVPR, 2017.

[7] ISIC Archive, International Skin Imaging Collaboration Dataset.

[8] Amazon Web Services, Machine Learning and Serverless Architecture Documentation.

[9] [9] Lachgar, M., Benouda, H., & Elfirdoussi, S. (2018, November). Android REST APIs: Volley vs Retrofit. In 2018 International Symposium on Advanced Electrical and Communication Technologies (ISAECT) (pp. 1-6). IEEE.

[10] U.-O. Dorj, K.-K. Lee, J.-Y. Choi, and M. Lee. The skin cancer classification using deep

convolutional neural network. Multimedia Tools and Applications, 77(8):9909–9924, 2018.

[11] Esteva, B. Kuprel, R. A. Novoa, J. Ko, S. M. Swetter, H. M. Blau, and S. Thrun. Dermatologist-level classification of skin cancer with deep neural networks. nature, 542(7639):115–118, 2017.

[12] H. A. Haenssle, C. Fink, R. Schneiderbauer, F. Toberer, T. Buhl, A. Blum, A. Kalloo, A. B. H. Hassen, L. Thomas, A. Enk, et al. Man against achine: diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition in comparison to 58 dermatologists. Annals of Oncology, 29(8):1836–1842, 2018.

[13] S. S. Han, M. S. Kim, W. Lim, G. H. Park, I. Park, and S. E. Chang. Classification of the clinical images for benign and malignant cutaneous tumors using a deep learning algorithm. Journal of Investigative Dermatology, 138(7):1529–1538, 2018.

[14] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 770–778, 2016a. K. He, X. Zhang, S. Ren, and J. Sun. Identity mappings in deep residual networks. In European conference on computer vision, pages 630–645. Springer, 2016b.

[15] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger. Densely connected convolutional networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 4700–4708, 2017.

[16] J. Kawahara and G. Hamarneh. Multi-resolution-tract cnn with hybrid pre-trained and skin-lesion-trained layers. In International workshop on machine learning in medical imaging, pages 164–171. Springer, 2016.

[17] D. P. Kingma and J. Ba. Adam: A method for stochastic optimization. arXiv:1412.6980, 2014. arXiv preprint

[18] Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In Advances in Neural Information Processing Systems, pages 1097–1105, 2012.

[19] R. Lopez, X. Giro-i Nieto, J. Burdick, and O. Marques. Skin lesion classification from dermoscopic images using deep learning techniques. In 2017 13th IASTED international conference on biomedical engineering (BioMed), pages 49–54. IEEE, 2017.

ACKNOWLEDGMENT

This work is part of my research carried out at **Jain (Deemed to be University), Karnataka, India**, under the guidance of **Dr. Devaraj Verma C**. I sincerely thank my research guide for his continuous support, valuable guidance, and encouragement throughout the course of this research.