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Cloud-Based Skin Cancer Diagnosis Using Convolutional Neural Networks with Efficientnet

[*1] Priyadarshini Radhakrishnan, [2]Yashwant Kumar Kolli, [3]Vijai Anand Ramar, [4]Karthik Kushala, [5]Venkataramesh Induru and [6]Thanjaivadivel M

[*1] IBM Corporation, Ohio, USA.

[2]Cognizant Technology Solutions US Corp, College Station, Texas, USA.

[3]Delta Dental Insurance Company, Georgia, USA.

[4]Taylor Corporation, Minnesota, USA.

[5]Piorion Solutions Inc, New York, USA.

[6]Nandha Engineering College, Erode, Tamil Nadu, India.

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***Corresponding Author**
Priyadarshini Radhakrishnan
IBM Corporation, Ohio, USA.

Abstract

The increasing incidence of skin cancer has called for the creation of early, accurate, and computerized diagnostic systems. Existing techniques often suffer from high error rates and limited preprocessing capabilities. To reverse this, work seeks to develop a deep learning model for the precise classification of skin disease from the International Skin Imaging Collaboration dataset for effective detection of malignant and benign lesions. The procedure starts by gathering skin cancer image data from the International Skin Imaging Collaboration dataset and performing preprocessing using Contrast Limited Adaptive Histogram Equalization and Gaussian filtering for noise removal and contrast enhancement of images are fed into a Convolutional Neural Network to receive features, subsequently, Efficient Net categorizes the inputs as non-cancer and cancer classes, and uploads non-cancer cases to a cloud storage system for convenient access and effective data management. Experimental tests validate the effectiveness of the system, where the Efficient Net classifier performs with better precision of 96.8%, accuracy of 95.4%, recall of 94.7%, and F1-score of 95%. The study offers a reliable framework that maximizes diagnostic reliability and availability since it is a notable contribution to intelligent healthcare solutions.

Keywords: Skin cancer detection, convolutional neural network (CNN), image preprocessing, medical image classification, automated diagnosis, and cloud integration

1. Introduction

Skin cancer is an extensive kind of cancer, and early discovery has to be ensured to maximize the rate of curing and survival [1]. Classical discovery is experience-based and bare-eye inspection, and is subject to easy variation and exaggeration. With the full maturity of medical image processing technology and artificial intelligence, computer systems can be utilized to aid dermatological diagnosis more strongly and equally [2]. On the basis of DL models, this research built a science and technology-oriented skin cancer diagnosis model by coupling image processing methods. The model is based on capturing the skin lesion images from conventional medical image databases, image pre-processing for enhancement, and examining the images using a CNN to extract deep-level features. Next, these features are sent through a classification model, which determines whether or not to predict cancer or no cancer in the lesion. The non-essential test reports are also uploaded to cloud storage to access them remotely, store them for long-term use, and integrate them with larger healthcare systems [3].

The suggested method of disease diagnosis based on medical imaging includes a logically organized sequence of processes that entails data acquisition, image processing, feature extraction, classification, and cloud data management. The images are accessed from common medical image databases, then pre-processed to improve image quality [4]. The contrast enhancement and noise removal enhance the separability of the involved features. High-level algorithms provide informative features, i.e., structural, textural, and shape-based features, from enhanced images. A classification model uses these characteristics to categorize images into appropriate diagnosis classes [5]. The outputs are processed for further action, and in case non-critical conditions are detected, the data is uploaded securely to a cloud platform for efficient healthcare provision and future use [6].

The suggested skin cancer detection model possesses a number of limitations that can influence its performance and applicability in real-world scenarios. The current dataset, i.e., International Skin Imaging Collaboration (ISIC) Archive, is class-imbalanced and underrepresented in terms of skin types, ages, and lesion classes [7]. Preprocessing tasks, i.e., denoising and contrast correction, distort important visual information inadvertently or introduce artifacts, which affect the feature extraction accuracy [8]. CNN interpretability is also compromised since the models are used as black-box systems, lowering the degree of confidence among the healthcare professionals. The ability of the models significantly relies on the quality of the input images, and problems such as low resolution, unfavorable illumination, or obstruction reduce the precision of prediction. Cloud integration is also a point of concern as far as data security, privacy, and compliance with healthcare regulations are concerned [9]. The model addresses binary classification and is not equipped with multiple subtypes of skin cancer, hence diluting its level of depth in diagnosis. To bridge such shortfalls is of the utmost importance to boost the credibility, safety, and scalability of AI skin cancer diagnosis systems [10].

- Develop an automated skin cancer detection framework that enhances diagnostic accuracy and reliability using preprocessing, DL, and cloud integration.
- Utilize the ISIC skin cancer dataset, consisting of various malignant and benign lesion images, for training and evaluating the proposed model.
- Enhance image quality and deep feature representation through Gaussian filtering, CLAHE, and CNN-based feature extraction.
- Integrate EfficientNet for high-precision classification and cloud storage for scalable, access, and long-term diagnostic data management.

The Structure of this paper is as follows: Section 2 gives the current skin cancer detection methods and their limitations are explained. Section 3 gives the system that has been proposed. Section 4 explains the result analysis, and Section 5 concludes with system efficiency and future improvements.

2. Literature Survey

H. Nagarajan *et al.* [11] worked with a cloud-based CNN architecture for detecting skin cancer from the ISIC database with preprocessing stages involving augmentation and normalization. Optimized using the Adam method, the model resulted in 99% accuracy superior to other known approaches like PSPNET-Fuzzy Logic and GBDT+ALBERT. Cloud infrastructure ensured scalability in terms of storage with increased healthcare coordination. J. Bobba [12], work researched a safe financial information sharing framework for hybrid cloud environments in the banking industry. It used info fusion together with ML and AI to ensure the data accuracy along with regulatory compliance. Integrating both public and private clouds helped increase security and protect sensitive financial information well. Earlier studies identified the application of machine learning and DL-based methods for health care fraud discovery. Methods used were logistic regression, decision tree, SVM, CNN, and RNN with the assistance of big data. The Decision Tree Classifier was as much as 99.9% accurate, indicating their effectiveness in identifying fraudulent activity.

K. Parthasarathy *et al.* [13], investigates the shortcoming of conventional encryption schemes such as AES and RSA for cloud-wide adoption and presents a homomorphic encryption scheme for secure computation on encrypted data with observations on security vs. efficiency trade-offs, research applied AI and ML techniques to improve care for the elderly through the use of predictive modelling to handle chronic illness and fall detection, which had high accuracy and reliability in ensemble methods. S. S. Kethu [14], research Health Fog is a hybrid IoT framework through fog computing, cloud computing, and DL to identify cardiac and infectious diseases in their initial stage with 94.5% accuracy and 0.08 seconds latency research to provide extra security to data in cloud environments by incorporating key management protocols, encryption stages, and performance improvement using OpenSSL and AWS KMS utilities, thus attaining high security and satisfactory computation performance, study posited a reliable IoT-cloud healthcare system that took into consideration the quality and scalability problems of health systems. Data preprocessing, safe storage capacity, and manageable encryption were included in the study for providing efficient, fault-tolerant, and scalable patient observation.

V. S. Musam *et al.* [15], work utilized deep models including Transformers, RNNs, and CNNs to apply on EHR and medical image-based clinical decision-making with a 91% success rate by means of transfer learning and application of XAI tool but was hampered by data privacy and clinical adoption issues study aimed at improving cost-effectiveness, scalability, and efficiency in cloud computing for managing an enormous amount of data by technology like load balancing, auto-scaling, and dynamic resource allocation with ensured data security, power management, and system stability. S. Narla *et al.* [16], work in MARS-based cloud-based predictive model development studies, Histogram-Based Gradient Boosting, and SoftMax Regression improved healthcare outcomes through the removal of big data issues, improved prediction accuracy, and the improved early disease and individualized treatment identification in elastic cloud settings. Research is moving to cloud computing and AI to totally transform customer relationship management and achieve data-driven insights based on the utilization of AI-based sentiment analysis in implementing AI-infused sentiment analysis, improving the interaction, satisfaction, and general performance of CRM operations.

M. R. Sareddy and S. Khan [17], work has proven the capability of AI to improve control over data as well as privacy in mHealth settings, up to 94% in precision when AI is used within secure, role-managed mobile healthcare settings. S. Narla *et al.* [18], Experiments proved that they ensure FogBus module connectivity and cloud federation that ensures IoT-based healthcare with reduced latency, energy, and wastage of data, improved scalability, resource management, and performance. Jyothi Bobba [19], Studies have increased the application of AI methods such as k-means clustering for removal of outliers and regression analysis to forecast maintenance in order to enhance IaaS and make it more compliant with financial information researched AVEC system, once hypothesized and emulated, exceeded the performance levels of standard SDN-OVS configurations under extensive cloud infrastructure adoption, providing larger throughput, better latency reduction, and efficient usage of resources for heavy loads, without such achievement in degraded performances in the previous study. S. Boyapati [20], Research has discovered that Cloud IoT can help lower income inequalities between urban and rural communities to a large extent, especially when used with sophisticated analytical methods, as per a study employing Explainable AI and statistical analysis.

2.1 Problem Statement

Skin cancer is an epidemic and a dangerous disease, and early diagnosis will guarantee successful management and improved survival [21]. Traditional practices such as naked-eye examination and clinical judgment are the pitfalls of being non-standardized and subjective in character. With the growing patient volume relentlessly increasing, volume-coping scalable, automatable, and reproducible solutions need to be applied [22]. Advances in DL and skin lesion image analysis have been accompanied by new opportunities but challenges in the attainment of useful skin lesion image processing and analysis systems at high accuracies [23]. These include skin lesion type heterogeneity, heterogeneity of image quality, as well as efficient feature extraction and classification systems [24]. The present work covers an intelligent system for skin cancer diagnosis based on image preprocessing and machine learning approaches like CNN for feature extraction and Efficient-Net for classification. Long-term storage of data as well as its management are made available through cloud storage [25].

3. Proposed Methodology

The process that is suggested to identify skin cancer is the sequential application of steps consisting of retrieving data, preprocessing, feature extraction, classification, and interactions with clouds. Images of skin lesions are available in the form of medical imaging datasets like the ISIC Archive, which were classified as either non-cancerous or cancerous lesions. These are pre-processed for better quality and uniformity by employing filters and CLAHE techniques for enhanced contrast. These are then shown to a CNN with the goal of feature learning, from where they give deep, abstract features like shape, edges, and textures. These features are input to an Efficient-Net model, and it classifies as either a cancer class or a non-cancer class. These attributes are computed based on the results, and upon the determination of being non-cancerous, this type of information is duplicated over a cloud storage where it is preserved, transmitted, or otherwise handled forward. Remote access to diagnostic reports and data management in the long term is enabled by this cloud integration. Figure 1 indicates the overall proposed method.

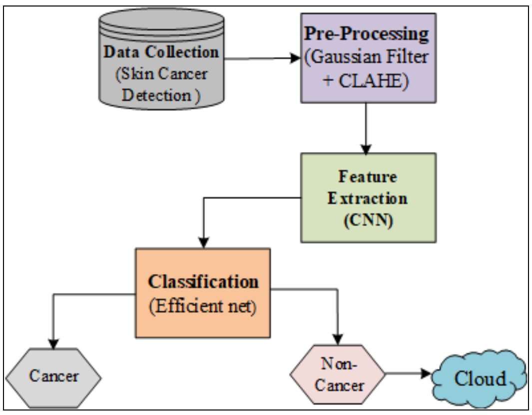

Fig 1: Skin Cancer Detection using CNN with cloud

3.1 Pre-Processing

Pre-processing is required for the detection of skin cancer to enhance the image quality as well as make the image homogeneous before the analysis by a DL algorithm. Sharpening of the image, removal of noise, and emphasis on contrast are carried out for the enhancement of other features. Techniques utilized in filtering are applied if the elimination of noise for the sake of retaining the edge of the lesion is essential. Contrast Enhancement and Feature Highlighting, like texture and color alteration, is attained by Limited Adaptive Histogram Equalization CLAHE. Normalization and pixel luminance resizing are done on all images to be the same throughout the data set so that it can deliver the same quality input to the CNN to improve the model for highlighting significant features and lesion classification.

3.2 Gaussian Filtering

The skin cancer images were obtained through noise suppression using Gaussian filter pre-processing techniques while keeping structural details. It is a linear smoothing filter which convolves an image with a Gaussian function, where a weight is assigned to a pixel near the center of the filter more than to the one that is farther away. The filter blurs any extraneous details, while at the same time keeping intact information about important features, such as edges and textures that are part and parcel of good classification. The Gaussian filter has a positive effect on the quality of the input data by removing high-frequency noise and, consequently, artifacts that could interfere with feature extraction by DL models. Particularly in medical imaging, that step allows for improvements in visibility by which medical diagnostics and features gain without distortions capable of misleading the classification model. The filtered images are then processed by contrast enhancement through CLAHE to give visibility in more contrast-critical lesion patterns. This combined pre-processing makes the input images easy to use for accurate feature extraction and classification by subsequent DL methods.

$$G(x,y) = \frac{1}{2\pi\sigma^2} \cdot e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

The formula of the Gaussian filter employs x and y as origin distances, σ (sigma) being the Gaussian distribution's standard deviation. Higher values of σ produce more blurring. The base of the natural logarithm in the formula's exponential function is Euler's number (e), approximately equal to 2.718.

3.3 Contrast-Limited Adaptive Histogram Equalization (CLAHE)

The CLAHE is used to improve the contrast of images for further evaluation of important features for the correct classification of skin cancer. CLAHE operates adaptively as it divides an image into smaller regions or tiles and improves the contrast in that tile separately, as well as includes a contrast limiting mechanism that prevents over-enhancement and noise amplification. They are subsequently merged with bilinear interpolation to give the final image a smooth transition. Therefore, this process has provided improvement in the quality of the medical images, making it easier for DL models such as DenseNet-121 to extract more relevant features for classification.

$$p(i) = \left\lfloor \frac{CDF(i) - CDF_{min}}{1 - CDF_{min}} \times (L-1) \right\rfloor \quad (2)$$

The pixel intensity $p(i)$, remapped following application of CLAHE is obtained based on the cumulative distribution function $CDF(i)$ of the intensity levels of the pixels within a local region in the image. This CDF is derived after clipping and redistribution of the histogram to prevent excess contrast enhancement and noise amplification. Normalization is performed by using the CDF_{min}, minimum non-zero intensity, and the entire range available for pixel intensity is set as the number of gray levels L, usually 256 in an 8-bit image.

3.4 Future Extraction

In the skin cancer detection approach proposed here, Convolutional Neural Network (CNN) is given a pivotal position in the step of feature extraction. Following the extraction of images of skin lesions from medical archives like the ISIC Archive and preprocessed by methods like filtering and CLAHE for improving image and contrast quality, they are input into a CNN. These pictures are distorted by CNN using a series of convolutions involving learnable filters (kernels) passing through the picture in the process of recognizing the local structures, including edges, texture, and shape.

Mathematically, each convolution operation is defined as

$$y(i,j) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} X(i+m, j+n) \cdot K(m,n) \quad (3)$$

Here, X is the input image patch K is the kernel and $Y(i,j)$ is the output feature value at position (i,j).

The CNN employs a Rectified Linear Unit (ReLU) activation function to enforce non-linearity for the network to be capable of learning medical image intricate patterns. The max pooling and similar pooling layers downsample spatial dimensions and reduce pertinent information after activation. The process of iteration repeats to derive abstract features.

$$f(x) = \max(0, x) \quad (4)$$

These continuous changes allow the CNN to learn a hierarchical deep representation of the image information, where closer layers learn general textures and boundaries and deeper layers specialize in structures and patterns of lesion types at higher levels. This leads to a rich compressed feature representation that can serve as a good input to the following stage of classification as well as the foundation of effective skin cancer detection.

The CNN learns hierarchical features by looking at the convolution and pooling operations and combining them into a one-dimensional vector representation. It represents the features as fully connected layers, where the neuron connects all elements of the vector. Layers are the classifiers that supply final output by collecting learned features. Weight and bias to every connection, and output is a linear combination of inputs. The output feature vector is for stable abstract skin lesion image features in stable classification.

$$y = W \cdot x + b \quad (5)$$

This formula computes the output by taking the weighted sum of inputs (x) and adding a bias term (b) to introduce flexibility in learning.

3.5 Efficient-Net Classification

Deep features are handled by an Efficient-Net model, being the main classifier instead of CNN for end-classification. Efficient-Net classifies cancerous or non-cancerous lesions from the obtained features. In case of non-cancerous results, results and metadata are saved to cloud infrastructure for remote access and long-term data handling. The combination boosts the accuracy and efficiency of the diagnostic system.

This project identifies skin cancer using an automated pipeline. The CNN model derives deep features of pre-processed lesion images and discloses visual features like edges, textures, and shapes. The Efficient-Net model classifies based on transferred features at high accuracy rates. Non-cancerous outputs can be saved to cloud storage as per the decision logic, enabling data management and remote healthcare services. This step enhances diagnostic uniformity and reduces labor and time to detect initial skin cancer, backed by the purpose of the project to develop a quick, accurate, and scalable solution.

3.6 Integration of Cloud Storage

For scalability, accessibility, and efficient data handling, the proposed system in this submission includes cloud storage as the core module. Following classification, the non-cancer patients are safely uploaded into the cloud for permanent data preservation and online access to healthcare specialists. This manner of data exchange in hospital coordination, and laying the groundwork for the development of an intelligent and networked healthcare infrastructure becomes feasible. In addition, cloud storage of results reduces local storage needs and allows diagnostic data to be accessed in the future for reference and analysis.

4. Result and Discussion

The recent approach to computer-aided detection of skin cancer involves a pipeline process for data collection, preprocessing, feature extraction, classification, and cloud integration. The system improves the brightness and uniformity of images of skin lesions with the help of preprocessing operations. CNN have been employed for deep feature extraction, and Efficient-Net has been applied as a classifier to discriminate cancerous and non-cancerous lesions. High accuracy, precision, sensitivity, F1-score, and Cohen's Kappa score are recorded by the model. The system is scalable, cloud-integrated, and of high accuracy.

4.1 Dataset Description

The data for this study contain 2,357 high-resolution dermoscopic images taken from the (ISIC). Both benign and malignant skin lesions are represented in the dataset, categorized and labeled in compliance with ISIC standards. The dataset is roughly balanced among the majority of the categories but shows a mild overrepresentation in terms of the quantity of melanoma and nevus (mole) images. The data set includes a broad spectrum of nine skin diseases, i.e., actinic keratosis, basal cell carcinoma, dermatofibroma, melanoma, nevus, pigmented benign keratosis, seborrheic keratosis, squamous cell carcinoma, and vascular lesions. This broad spectrum allows for strong training and testing of the introduced skin cancer detection model.

Link: https://www.kaggle.com/datasets/nodoubttome/skin-cancer9-classesisic

4.2 Performance of the Proposed Framework

Performance measurement highlighted precise classification between cancer and non-cancer cases. Minimal misclassification was shown by the confusion matrix, and strong and consistent detection performance were confirmed through significant metrics. The model as a whole exhibited high generalization capability and performance for a variety of skin lesion types.

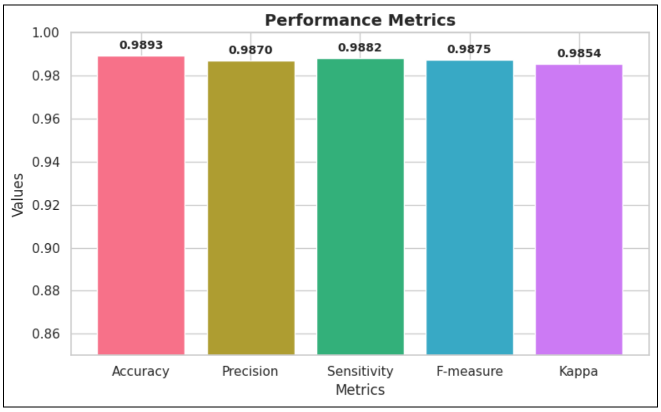

Fig 2: Performance Evaluation Metrics of the Proposed Skin Cancer Detection Framework

Figure 2 shows the major performance metrics achieved by the proposed skin cancer detection system. The model achieves improved predictive precision of 98.93% with evidence from high precision (98.70%), sensitivity (98.82%), and F-measure (98.75%), which demonstrate well-calibrated performance as a function of true positives over false negatives. A Kappa measure of 98.54% further presents high agreement between the predicted and real classes, indicating the trustworthiness of the classification. These results confirm the validity and reliability of the approach to detect malignant and benign skin lesions.

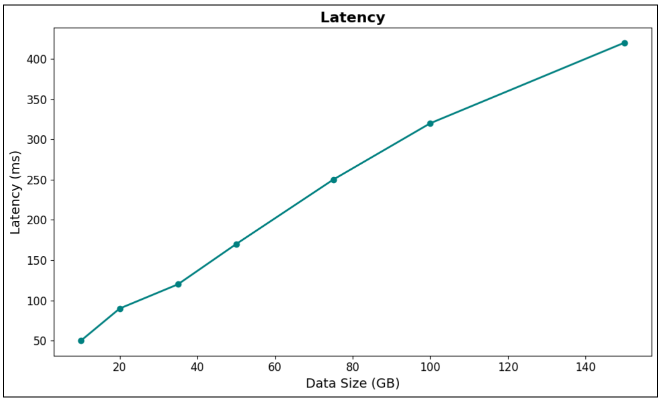

Fig 3: Latency Variation in Cloud-based Skin Cancer Detection System

Figure 3 shows the performance of latency in the proposed skin cancer detection cloud-integrated system as the size of the data is varied. It shows a pattern of linear increase in latency and thus proves to be low when the data is small, but diminishes gradually when the input increases in size. This is to be expected in cloud infrastructure, where the increase in data transport and processing costs goes up with the growth in dataset size. Although increasing, the latency is still in acceptable limits for non-emergency medical diagnoses, justifying the applicability of the system to remote, scalable healthcare solutions.

Conclusion

In this work, an Automated Skin Cancer Detection System to help in timely and accurate diagnosis. The model performed well, having an accuracy of 98.93%, precision of 98.70%, a sensitivity of 98.82%, and an F1-score of 98.75%. These outcomes confirm the functioning of the system in accurately classifying malignant and benign skin lesions. Low rate of misclassification, as seen in the confusion matrix, indicates the high reliability of the system for actual usage. Additionally, a high Kappa statistic of 98.54% is proof of consistent agreement between predictions and actual diagnoses. These statistics reveal that the model is consistent and can be applied in scalable, healthcare applications. Future improvements can involve increasing the data set to cover more skin diseases and modifying the system to be deployed on mobile devices to enable remote diagnosis. It is also possible to incorporate Explainable AI (XAI) for enhancing interpretability and building confidence in medical professionals.

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