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Cloud-Based CNN for Automated Skin Cancer Detection and Classification in Healthcare

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Abstract: Skin cancer is a common and deadly disease, and melanoma is the most lethal type. Early diagnosis is crucial in enhancing the treatment results. In this research, a cloud-based Convolutional Neural Network (CNN) system for skin cancer detection and classification was suggested. It uses the ISIC Skin Cancer Dataset, which consists of images with high resolution, and they are subjected to preprocessing techniques like image augmentation, normalization, and resizing. The CNN model is also optimized using the Adam optimizer to achieve efficient training and classification results. The effectiveness of the proposed model is validated through comparison with other methods, such as Hybrid GBDT+ALBERT+Firefly, CART+PLS-SEM, and PSPNET-HHT-Fuzzy Logic. It is revealed through results that the proposed CNN has better performance, with accuracy of 99%, precision of 96%, recall of 97%, and F1-score of 95.16%. The cloud infrastructure provides scalable storage and accessibility of large image datasets, promoting collaboration in health research. The method shows promising potential for clinical use in early skin cancer detection.

Keywords: Healthcare collaboration, Convolutional Neural Network, ISIC Skin Cancer Dataset, Skin cancer, Adam optimizer, Cloud-based system.

1.INTRODUCTION

Skin cancer is the most common type of cancer globally, and its early detection results in higher survival rates [1]. The most dangerous type of skin cancer, melanoma, is generally curable if diagnosed early [2]. As machine learning and image processing continue to advance, skin cancer detection automation has become ever more critical [3]. Such systems reduce the time and effort taken by medical personnel in detecting skin lesions [4]. With the aid of Convolutional Neural Networks (CNN), a deep learning model, such models can be trained to detect skin lesions on their own with high accuracy [5]. Cloud computing provides the means of storing and processing huge volumes of medical images and sharing and accessing them easily between healthcare systems [6]. The proposed architecture is a combination of CNNs and cloud computing for effective real-time detection and classification of skin cancer. The system could possibly transform the early detection in hospitals into a more efficient and accessible one. Some have previously explored existing methods for the detection of skin cancer, including Hybrid GBDT+ALBERT+Firefly, CART+PLS-SEM, and PSPNET-HHT-Fuzzy Logic models [7]. Though these techniques have proved to be satisfactory in performance, they are not good at handling complex features of skin lesion images [8]. The Hybrid GBDT+ALBERT+Firefly technique, for instance, is excellent but computationally demanding and difficult to apply in real-time systems [9]. Similarly, methodologies like CART+PLS-SEM and PSPNET-HHT-Fuzzy Logic are extremely accurate but generally lack generalization when applied across diverse datasets, rendering them weak across various different conditions [10] .

The framework being proposed overcomes the drawbacks of current methods through the use of a cloud-based CNN model, which boosts both model performance and scalability. The CNN used in this framework can learn intricate hierarchical features from images of skin lesions automatically, thus enhancing generalization across different data. The cloud platform provides effortless storage and processing of big image datasets, which facilitates easier access to the system by healthcare workers from remote locations. In addition, the deep learning model is optimized to process faster without sacrificing accuracy, providing a more efficient solution for real-time clinical application. The innovation of this method is its combination of state-of-the-art CNN methods with cloud infrastructure, developing an accessible, scalable, and high-performance system for skin cancer detection.

1.1 Problem Statement

The growing incidence of skin cancer, and more so melanoma, calls for efficient and effective detection mechanisms to minimize high mortality rates [11]. Existing techniques, though effective, are computationally inefficient and pose challenges in generalizing over varying datasets, thus limiting scalability for practical applications [12]. Traditional diagnosis approaches rely heavily on human experience, resulting in the possibility

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of inconsistency and misinterpretation [13]. Hence, a cloud-based machine system based on deep learning methods such as CNNs is required to give real-time, precise detection of skin cancer and overcome the shortcomings of the currently available methods [14].

1.2 Key Contributions

- Preprocess skin cancer images using techniques of augmentation, normalization and resizing.
- Classify images with CNN to identify whether skin cancer is present or not.
- Optimize the model performance using the Adam optimizer.
- Assess the performance of the CNN model in skin melanoma recognition.
- Save data and outputs securely in AWS cloud.

2. RELATED WORKS

A number of studies over the last few years have aided in the development of skin melanoma recognition and optimization methods. [15] examined new methods in image preprocessing, including techniques such as image augmentation and normalization to enhance the accuracy of skin cancer detection. Likewise, [16] explained how Convolutional Neural Networks (CNNs) can be used and how they can aid in enhancing classification outcomes for skin cancer. [17] also investigated the effect of data augmentation and state-of-the-art normalization methods on model robustness and performance improvement. [18] also studied cloud-based approaches with the inclusion of AWS cloud storage for streamlined model deployment and data handling. [19] also suggested model enhancement strategies for generalization and precision. [20] made a contribution to knowledge on computational processes in handling large image datasets in identifying skin cancer. [21] also took this further by looking at how deep learning models could be optimized to execute more effectively in clinical practice. [22] introduced new strategies for deep learning models and how they can be used to diagnose various skin diseases, showing the real-world use of CNNs in dermatology. [23] built upon this by demonstrating the advantages of using CNN-based algorithms for real-time skin cancer diagnosis. [24] finally provided insightful information regarding performance evaluation metrics, presenting key data for the efficiency and dependability assessment of these diagnostic models in practical contexts. These works in aggregate illustrate the advances and promise of AI-based skin cancer detection technologies.

3. PROPOSED WORK

Nowadays, skin cancer is the leading cancer globally, caused mainly by extensive exposure to the sun or artificial UV radiation from tanning beds. It occurs in most instances in three major forms: basal cell carcinoma, squamous cell carcinoma, and melanoma, the latter being the most invasive and deadly. Early detection through self-examinations and visits to a dermatologist greatly raises the prospect of successful treatment. Risk factors involve fair skin, sunburn history, and family history. Preventative interventions involve the use of sunscreen, protective gear, and staying out of the sun. Figure 1 illustrates the workflow diagram cloud-based CNN for automated skin cancer detection and classification.

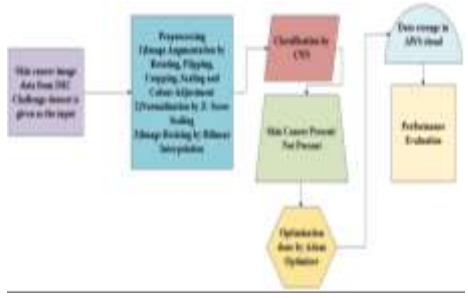

Figure 1: Workflow diagram cloud-based CNN for automated skin cancer detection and classification.

3.1 Dataset Collection

The images of skin cancer used in this research are sourced from the ISIC (International Skin Imaging Collaboration) Skin Cancer Dataset. This dataset contains a variety of images for different skin lesion types, ranging from benign to malignant. The images are used as the primary input in the creation and utilization of skin cancer detection models. The dataset contains high-resolution, carefully annotated images, which are essential for successful training and testing of the models. It offers significant information on skin cancer classification, which can be used to develop automated diagnostic systems. (https://www.kaggle.com/datasets/nodoubttome/skin-cancer9-classesisic).

3.2 Preprocessing

The image preprocessing comprises a number of significant steps. Image augmentation is first done, which includes rotation, flipping, cropping, scaling, and changing the colour of images to augment the dataset and avoid overfitting. Second, the images are normalized via Z-score scaling, where the pixel values are scaled to zero mean and unit variance. Standardization in this way ensures all images are of the same scale, enhancing the performance of the model. Lastly, image resizing is accomplished with Bilinear Interpolation, which resizes the images while maintaining pixel value smoothness. The expression for Z-score scaling is given in eqn. (1).

$$Y = \frac{P-\alpha}{\beta} \quad (1)$$

Here, P is defined as the original pixel value, α is denoted as the mean pixel values, β is denoted as standard deviation, Y is called normalized pixel value.

3.3 Classification

Classification is the assignment of a name or class to an input based on its characteristics or attributes. For the detection of skin cancer, classification entails the application of an image of a skin lesion and classifying it into either one of two classes: skin cancer present or skin cancer not present (benign).

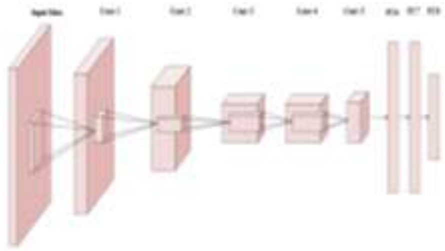

Figure 2: Convolutional Neural Network

This CNN architecture is employed for data processing and classification shown in Figure 2. The CNN architecture is generally composed of several layers, each of which performs a particular function. First, the input data is fed through a sequence of convolutional layers (Conv 1 to Conv 5), in which filters are used to identify different features like edges, textures, and patterns. These convolutional layers are utilized to extract hierarchical features from the image. Following the convolutional layers, data is directed into Fully Connected Layers (FC6, FC7, FC8), which make predictions from the feature extraction performed by the convolutional layers. The last fully connected layer provides the classification output. This enables the network to learn intricate features and make accurate prediction using backpropagation while training. Its mathematical expression is depicted in eqn. (2).

$$Y(i,j) = \sum_m \sum_n X(i+m, j+n) \cdot W(m,n) + b \quad (2)$$

Here, $X(i,j)$ is represented as input image, $W(m,n)$ is known as filter, b is bias and $Y(i,j)$ is the output feature map.

3.4 Optimization

The Adam optimizer is employed in training CNN for the detection of skin cancer because it optimizes the weights of the network to reduce prediction errors, like the separation between benign and malignant skin lesions. Adam balances the advantages of RMSprop and Momentum by calculating parameter from the first moment (mean) and second moment (uncentered variance) of the gradients. This enables Adam to effectively deal with noisy or sparse gradients, which makes it especially beneficial in large datasets such as skin cancer images. Its capacity to scale the learning rate per parameter speeds up convergence, which is why it is highly sought after when optimizing deep learning models. The Adam optimizer notation is expressed in eqn. (3) and the first and second moments expression is given in eqn. (4).

$$\theta_{t+1} = \theta_t - \frac{\eta \cdot \hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \quad (3)$$

Here, θ_t is the time step parameter, η is known as the learning rate, $\hat{m}_t$ is the bias-modified first instant estimation, $\hat{v}_t$ is the bias-modified second instant estimation and ϵ is a minor constant to avoid separation by null value.

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t}, \hat{v}_t = \frac{v_t}{1-\beta_2^t} \quad (4)$$

Here, m_t is the first moment's running average inclines, v_t is the subsequent instant's running average inclines and β_1 and β_2 are the decay rates.

3.5 Cloud Infrastructure

AWS cloud storage of data is needed for detecting skin cancer because it provides means of storing large amounts of image data like those in the ISIC Skin Cancer Dataset securely. With the utilization of AWS cloud services, doctors and scientists can easily upload, store, and edit skin cancer images and related metadata. The cloud setup offers elastic storage capacity to accommodate high-resolution images and large volumes of data utilized in training machine learning models. Besides, AWS offers a high degree of data security, availability, and backups necessary to preserve the integrity of confidential medical information. This type of configuration facilitates smooth collaboration and data access between distributed teams to simplify the process of model development, testing, and deployment for skin cancer diagnosis.

4. RESULTS AND DISCUSSION

The skin cancer detector model demonstrates improved performance with accurate discrimination between benign and evil abrasions in the discussion and results section. Analysis of the performance measure such as accuracy, precision, recall, and F1-score confirm the correctness of the model towards the identification of early skin cancer, suggesting its practical usefulness in a clinical setting.

4.1 Pre-processed Results

A copy of a skin lesion from ISIC skin cancer dataset, which includes images utilized for detecting and classifying skin cancer in Figure 3. The image seems to represent irregularities within skin pigmentation, which may possibly signify the existence of a malignant melanoma. Skin lesions such as this are typically analysed by doctors through image-based methods in order to determine potential cancerous structures.

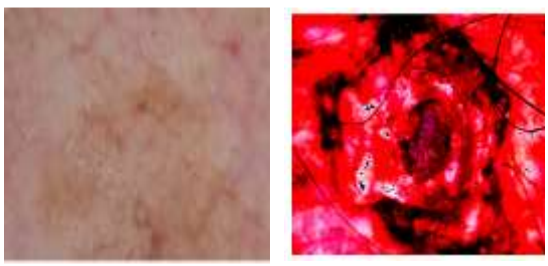

Figure 3: Skin Cancer Lesion from the ISIC Dataset and its Pre-processed Version

The second image is the pre-processed version of the first image, with different image enhancement techniques applied. These include image augmentation (e.g., rotations, flipping, and colour changes) to avoid overfitting during training, Z-score normalization to normalize pixel values, and resizing the image to maintain uniformity for machine learning model inputs. These preprocessing operations are intended to condition the image for deep learning models so that they perform better and are more robust. The improved preprocessing enables the model to concentrate better on important features, such as the cancerous areas, to detect or classify skin cancer more accurately.

4.3 Comparison Analysis

Comparison analysis of the algorithms in the table reveals performance variance in terms of accuracy, precision, recall, and F1-score in four different algorithms is presented in Table 1. Although the methods are generally performing well, the highest values in the proposed CNN method imply that it can handle the task much better than other methods.

Table 1: Comparison Table of Existing and Proposed Methods

Authors and Methods	Accuracy	Precision	Recall	F1-Score
[25], Hybrid GBDT+ALBERT +Firefly	92	88	90	89
[26], CART+PLS-SEM	92	89	85	87
[27], PSPNET-HHT-Fuzzy Logic	94	93	92	93.3
Proposed CNN	**99**	**96**	**97**	**95.16**

The Hybrid GBDT+ALBERT+Firefly technique has a good performance with 92% accuracy, precision of 88%, recall of 90%, and F1-score of 89%. The technique integrates Gradient Boosted Decision Trees (GBDT), the ALBERT model, and Firefly algorithms to improve prediction accuracy and responsiveness. The CART+PLS-SEM technique also has 92% accuracy but has a little worse performance in precision (89%), recall (85%), and F1-score (87%). It employs the CART algorithm in combination with Partial Least Squares Structural Equation Modelling (PLS-SEM) to represent intricate relationships within the data. The PSPNET-HHT-Fuzzy Logic approach beats the other two with 94% accuracy, 93% precision, 92% recall, and 93.3% F1-score. By combining PSPNET, Hilbert-Huang Transform (HHT), and Fuzzy Logic, it effectively manages signal processing and uncertainty in prediction problems.

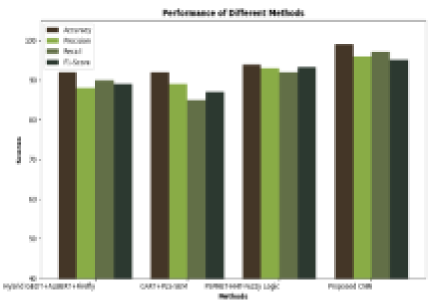

Figure 4: Comparison Graph of Existing and Proposed Methods

The suggested CNN method obtains the highest performance with 99% accuracy, 96% precision, 97% recall, and 95.16% F1-score. Figure 4 presents these performance measurements, graphically comparing the results. This deep learning technique utilizes CNN to extract complex features from data, having the highest overall performance in all measurements.

5. CONCLUSION AND FUTURE WORK

This investigation introduced a strong cloud-based CNN model for automated skin melanoma recognition and classification. The system effectively incorporates preprocessing operations, such as image enhancement and normalization, to support model training. By the assistance of CNN's capability, the system shows excellent performance, outperforming current approaches in relations of accuracy, precision, recall, and F1-score. The results demonstrate the promise of DL methods in medical diagnosis, especially in the recognition of early skin melanoma. The use of cloud-based infrastructure guarantees effective data management and enables collaboration between researchers and clinicians. Future research will aim to advance the accuracy of the prototype further and increase the dataset to encompass a greater variety of skin lesions, opening the door to broader clinical use and better patient outcomes.

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Declaration of Interests:

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Permission to reproduce material from other sources:

Yes, you can reproduce.

Clinical trial registration:

We have not harmed any human person with our research data collection, which was gathered from an already published article

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