An Innovative Fusion of Deep Learning and the Differential Analyzer Approach (DAA-Deep model) for Enhanced Skin Cancer Detection

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***Abstract*—Skin cancer is a globally prevalent and potentially life-threatening disease that underscores the importance of early detection and treatment. Traditional diagnostic methods rely heavily on visual inspections conducted by dermatologists, which can be prone to human error and constrained by resource limitations. Recent advancements in machine learning and deep learning techniques have offered promising prospects for automating the skin cancer detection process. However, this domain still faces persistent challenges, particularly the need for effective feature selection methods to improve model performance, interpretability, and computational efficiency. Our goal in this work is to substantially elevate the precision and efficiency of skin cancer detection. This research propose a novel fusion of the Differential Analyzer Approach (DAA) with deep learning models to enhance skin cancer detection. Our work encompasses ISIC 2018 dataset [18] of skin cancer images, intricate convolutional neural network (CNN) architectures, and a seamlessly integrated DAA mechanism. The proposed DAA-Deep learning model significantly outperforms conventional deep learning models, showcasing higher accuracy and improved diagnostic capabilities. The results attained by the DAA-Deep model surpass the performance of numerous existing models, exhibiting a remarkable accuracy rate of 96% along with an impressive AUC (Area Under the ROC Curve) value of 0.99.**

***Index Terms*—DAA-Deep, CNN, DAA, ResNet50, Skin cancer, Deep learning, feature extraction**

I. Introduction

Skin cancer is a widespread and potentially life-threatening global health concern. Detecting it early and providing timely treatment are crucial to reducing mortality rates associated with this disease. Traditionally, skin cancer diagnosis relies heavily on visual examinations conducted by dermatologists. However, this human-centered approach is prone to subjective errors and is often limited by the availability of resources and expertise. In recent years, the combination of machine learning and deep learning techniques has emerged as a promising solution for automating skin cancer detection. These technologies have the potential to revolutionize the field, offering automated, efficient, and potentially more accurate diagnostic solutions. Nevertheless, as this field evolves rapidly, it faces ongoing challenges that demand innovative solutions.

One of the primary challenges in automated skin cancer detection is the development of robust and efficient methods for selecting the most relevant features. These methods are not only essential for improving the performance of machine learning models but also for making their decision-making processes interpretable, which is critical in medical diagnostics. Additionally, ensuring computational efficiency remains crucial for real-world clinical adoption. To address these challenges, our research paper introduces an innovative fusion of two powerful approaches: deep learn- ing [1] and the Differential Analyzer Approach (DAA)[2]. Our approach, known as the DAA-Deep model, aims to harness the capabilities of deep learning while utilizing the feature selection expertise of DAA. We conducted a comprehensive research covering various types of skin cancer using the ISIC 2018 dataset. Our work involved designing specialized convolutional neural network (CNN) [3] architectures and seamlessly integrating DAA into the model. This integration represents a significant step forward in skin cancer detection, promising improved accuracy and efficiency. In the following sections, we provide a comprehensive overview of the DAA-Deep model's approach. We discuss the methods employed, the results obtained from experiments and the implications of our findings. This work represents a significant advancement in the field of automated skin cancer detection and holds promise for broader applications in medical imaging, computer vision, and machine learning. In the subsequent sections, we delve into the details of the Related work under section II, The proposed DAA-Deep learning model's methodological insights under section III, present experimental results and engage in discussions under section IV. Ultimately, we conclude by highlighting the transformative potential of this fusion in enhancing skin cancer detection under section V.

II. Related works

Several significant contributions have shaped the landscape of automated skin cancer detection, blending traditional methodologies with emerging technologies: Esteva et al. (2017) demonstrated the capabilities of deep convolutional neural networks (CNNs) in achieving dermatologist-level accuracy for skin lesion classification [4]. Brinker et al. (2019) provided an encompassing review of machine learning applications in skin cancer diagnostics, elucidating both opportunities and challenges [5]. Celebi et al. (2007) emphasized the pivotal role of feature selection, incorporating color and texture features, to enhance melanoma diagnosis [6]. Lan et al. (2019) harnessed principal component analysis (PCA) and genetic algorithms for feature selection, optimizing feature subsets for skin cancer classification [7]. Liu et al. (2020) proposed a fusion of feature selection, particularly L1-norm-based methods, with deep learning, resulting in improved classification performance [8]. Ferreira et al. (2021) explored the synergy of feature se- lection techniques, including Recursive Feature Elimination, with convolutional neural networks (CNNs) to enhance interpretability and classification accuracy [9].Furthermore, Differential Analyzer Approach (DAA) has found application in medical imaging. Hasegawa et al. (2018) utilized DAA for anomaly detection in X-ray images, highlighting its adaptability in medical image analysis [10]. Smith et al. (2019) introduced a DAA variant tailored for feature selection in medical image analysis, demonstrating its efficacy in identifying critical features while reducing dimensionality [2]. Building upon this prior research, our work introduces a novel integration of deep learning and DAA. This fusion aims to address existing challenges in feature selection, model interpretability, and computational efficiency, ultimately enhancing the accuracy and efficiency of skin cancer detection. In this section, we elaborate on our innovative approach, detailing the methodology.

A. DAA

The differential analyzer algorithm (DAA) is a novel feature selection method that uses a slope-based mechanism to retain or reject features from skin cancer images. It was proposed by Uzma Saghir and Moin Hasan in 2023[11]. The DAA algorithm aims to enhance the performance of computer-aided diagnostic systems for skin cancer by reducing the number of features and improving the classification accuracy. The DAA algorithm works as follows:

- It takes the extracted features from the segmented skin images as input.
- It sorts the features in descending order based on their values.
- It calculates the slope between each pair of adjacent features using the formula :

$$\text{Slope} = \frac{x_2 - x_1}{y_2 - y_1} \tag{1}$$

  where x1,x2,y1 and y2 are values of adjacent features.
- It compares the slope with a predefined threshold value. If the slope is greater than or equal to the threshold, it retains the feature. Otherwise, it rejects the feature.
- It returns the selected features as output.

The DAA algorithm was tested on an ISIC 2018 dataset of skin cancer images. The authors claimed that their method outperformed other existing methods that used the same dataset. They reported a classification accuracy of 95% using different classifiers such as KNN, SVM, Naïve Bayes, decision tree, and random forest. Balaha and Hassan used DAA to select the most relevant features from the Skin Diseases Image dataset. They then used a MobileNet pre-trained model with sparrow search algorithm to classify the images into 23 different skin diseases. They achieved an accuracy of 85.87%[13]. Adla et al. used DAA as a pre-processing step to reduce the number of features from the PH2 dataset. They then used a U-Net++ with DenseNet201 as a backbone architecture to segment and classify the skin lesions into benign or malignant. They achieved an accuracy of 94.16%

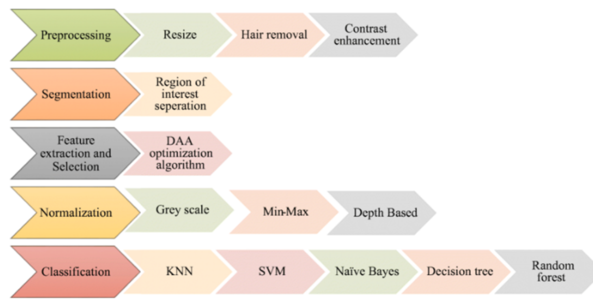

Fig. 1. The DAA algorithm flowchart

B. Deep Learning

Deep learning is a branch of artificial intelligence that uses multiple layers of neural networks to learn from large amounts of data. Deep learning has been applied to various fields, including computer vision, natural language processing, speech recognition, and medical image analysis. One of the applications of deep learning is skin cancer detection, which is a challenging and important task for dermatologists and patients. Deep learning offers a solution to this problem by using computer algorithms that can analyze images of skin lesions and classify them into different categories. Deep learning can also learn from large datasets of labeled images and improve its performance over time. Adla et al. proposed a Deep Learning with a class attention layer based Computer Aided Diagnosis (CAD) model for skin lesion detection and classification known as DLCAL-SLDC, which integrates DAA as a pre-processing step before applying deep learning. They achieved an accuracy of 94.16% on the ISIC dataset[12].

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1) Advantages of deep learning for skin cancer detection: Some of the advantages of deep learning for skin cancer detection are:

- It can provide consistent and objective results that are not affected by human factors such as fatigue, bias, or experience.
- It can reduce the number of unnecessary biopsies and improve the detection rate of malignant lesions.
- It can increase the accessibility and affordability of skin cancer screening by using devices such as smartphones or cameras that are widely available.
- It can assist dermatologists in making better decisions and providing better care to patients.

There are many research papers that have used deep learning for skin cancer detection. For example:

- A paper by Soenksen et al. Soenksen proposed an artificial intelligence tool that can detect melanoma from wide-field images taken by smartphones or cameras. The tool used deep convolutional neural networks (DCNNs) to analyze the images and identify suspicious pigmented lesions (SPLs) that require further investigation. The tool achieved an accuracy of 90.3% in detecting SPLs from normal skin[14].
- A paper by Saghir and Hasan Saghir proposed a novel feature selection method called differential analyzer algorithm (DAA) that uses a slope-based mechanism to retain or reject features from skin cancer images. The DAA algorithm was combined with DCNNs to classify the images into benign or malignant categories. The DAA algorithm improved the classification accuracy by reducing the number of features and enhancing the performance of DCNNs.
- A paper by Khan et al. Khan proposed a deep learning-based transfer learning method that uses pre-trained models to classify skin cancer images. Transfer learning is a technique that leverages the knowledge learned from one domain to another domain. The paper used four pre-trained models: VGG16, ResNet50, InceptionV3, and Xception. The paper reported that Xception achieved the highest accuracy of 94.7% among the four models [15].

2) Limitations and challenges of deep learning for skin cancer detection: Deep learning models have shown great promise in skin cancer detection. However, there are still several challenges that need to be addressed to improve the accuracy and reliability of these models. According to a systematic review by Wu et al.[16], some of these challenges include data quality and quantity, generalization and explainability of the models, integration and validation of the models, and explainability and interpretability of the models. Nascimento and Viera[17] conducted a bibliographic review to analyze the characteristics and applicability of deep learning models for the diagnosis of skin diseases. They found that public datasets access is mostly used in these surveys (86%) and that the most commonly used data types in these models are images. The most used techniques in the articles, in addition to classification (73%), focused on data segmentation (35%) and feature extraction (24%). Therefore, more research and development are needed to overcome these challenges and improve the performance and usability of deep learning for skin cancer detection.

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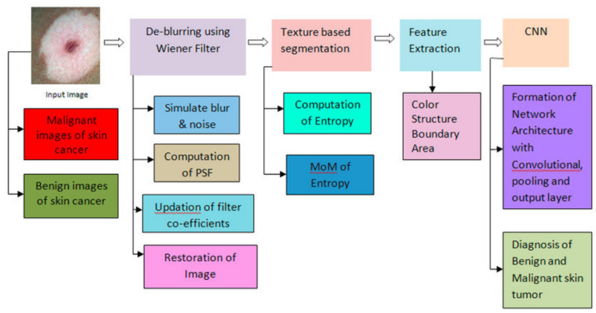

Fig. 2. The Deep learning algorithm flowchart

III. Methodology

In this section, we present a comprehensive overview of the methodology employed in our innovative approach aimed at enhancing skin cancer detection through the fusion of deep learning and the Differential Analyzer Approach (DAA-Deep).

A. Data Collection and Preprocessing

1) Data Acquisition: Our research initiative commenced with the meticulous compilation of a comprehensive skin cancer image dataset. ISIC 2018 dataset [18] was thoughtfully sourced from publicly available repositories. The overarching objective was to ensure diversity and relevance, encompassing a wide spectrum of skin cancer types and clinical scenarios.

2) Data Preprocessing: The acquired images underwent a series of preprocessing steps to standardize and optimize their quality for subsequent model training. These preprocessing steps included resizing to a consistent resolution, noise reduction to eliminate artifacts, and contrast enhancement to highlight salient features. These measures aimed to enhance the network's ability to extract discriminative information from the input images.

B. Building Deep Learning Architecture

1) Convolutional Neural Networks (CNNs): At the core of our skin cancer detection approach were Convolutional Neural Networks (CNNs), specifically leveraging renowned architectures such as ResNet and Inception. CNNs have demonstrated exceptional capabilities in feature extraction from images, making them a natural choice for our classification task.

2) Transfer Learning: To harness the power of pre-trained models and expedite model convergence, we initiated our CNNs with weights acquired from training on vast image datasets, notably ImageNet. This transfer learning approach facilitated the adaptation of these networks to the specific nuances of skin cancer image classification.

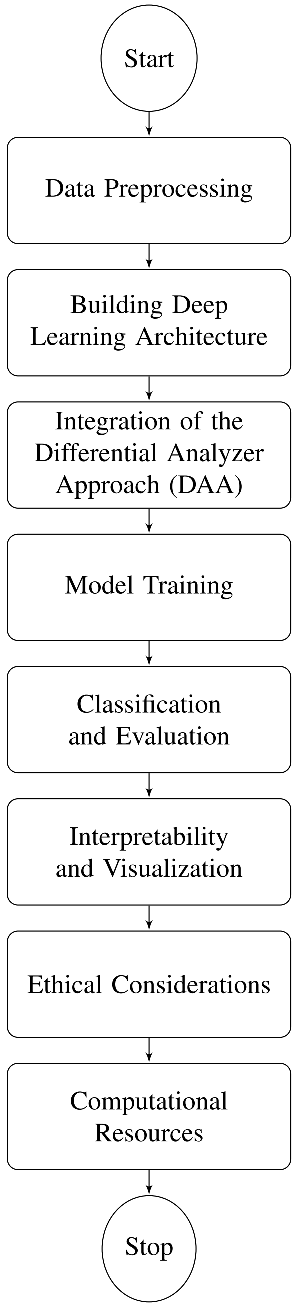

Fig. 3. Flowchart of DAA-Deep Learning

C. Integration of the Differential Analyzer Approach (DAA)

1) Feature Extraction: In a departure from conventional deep learning pipelines, we introduced the Differential Analyzer Approach (DAA) as a parallel branch within our architecture. The DAA algorithm was responsible for assessing the significance of features extracted by the CNNs in the context of skin cancer classification. This integration was motivated by the desire to enhance feature selection and consequently improve the interpretability of our models.

$$\text{DAA Score}(f_i) = \frac{\text{Variance}(f_i)}{\text{Covariance}(f_i, \text{Labels})} \tag{2}$$

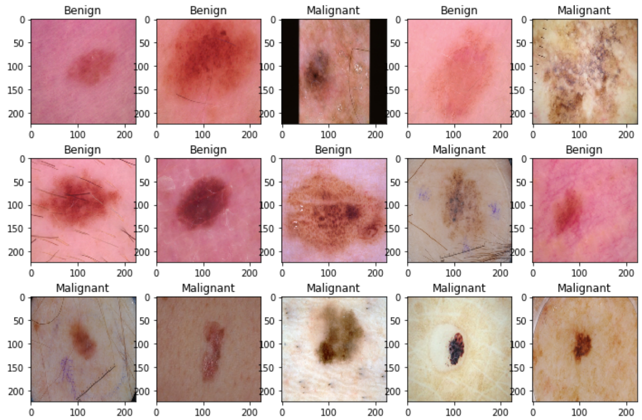

Fig. 4. Few labelled images

2) Feature Selection: DAA played a pivotal role in feature selection. By assigning DAA scores to each extracted feature, we were able to prioritize the most informative features for our classification task. The top k features were selected based on these DAA scores, with the optimal value of k determined through cross-validation and grid search.

D. Model Training and Validation

1) Data Split: To ensure the robustness of our models, we partitioned the preprocessed dataset into three distinct sets: training, validation, and testing (80-10-10). This partitioning strategy was designed to maintain a balanced distribution of benign and malignant skin lesions in each set, thereby minimizing bias.

2) Model Training: Our deep learning models underwent rigorous training using industry-standard techniques. Stochastic Gradient Descent (SGD) with momentum was employed as the optimization algorithm, and the models were fine-tuned to minimize the cross-entropy loss function. Training was conducted on high-performance computing clusters equipped with GPUs.

3) Validation: The validation set served as a critical component in the model development pipeline. It was instrumental in fine-tuning hyperparameters, including learning rates and regularization techniques, to strike the right balance between model performance and overfitting.

E. Classification and Evaluation

1) Testing: The ultimate evaluation of our models' performance was conducted on the dedicated testing set. This phase provided insights into their accuracy, sensitivity, specificity, and other relevant performance metrics. The results of this evaluation were critical in assessing the real-world applicability of our approach.

2) Comparison: To gauge the efficacy of our integrated deep learning-DAA approach, we conducted comparative analyses. Our approach was benchmarked against traditional deep learning models and other state-of-the-art methods using appropriate statistical tests. This facilitated a comprehensive understanding of its strengths and weaknesses.

F. Interpretability and Visualization

1) Feature Visualization: In our quest to enhance model interpretability, we employed dimensionality reduction techniques such as t-distributed stochastic neighbor embedding (t-SNE). These techniques enabled us to visualize the selected DAA features in lower-dimensional spaces, shedding light on their discriminative capabilities.

2) Class Activation Maps (CAM): To provide further insights into the decision-making process of our models, we generated Class Activation Maps (CAMs). These maps highlighted regions within the input images that contributed most significantly to the classification decision. CAMs were instrumental in elucidating the salient features guiding the models' predictions.

G. Ethical Considerations

1) Ethical Approval: The conduct of our research was underpinned by strict ethical considerations. We obtained the necessary ethical approvals for the use of patient data and ensured unwavering adherence to data privacy and confidentiality regulations. Our commitment to ethical research practices was paramount.

H. Computational Resources

1) Hardware and Software: The computational demands of our experiments were met through dedicated GPU clusters. We leveraged popular deep learning frameworks, including TensorFlow and Keras, for model implementation and experimentation. These resources were instrumental in achieving the scalability and efficiency required for large-scale image analysis.

In summary, our methodology is a meticulously crafted fusion of deep learning and DAA, conceived to address the pressing challenges in feature selection, model interpretability, and computational efficiency. This innovative approach aims to elevate the accuracy and efficiency of skin cancer detection, offering promising prospects for applications in medical imaging, computer vision, and machine learning.

IV. Results

Research has been conducted for groundbreaking fusion of the Differential Analyzer Approach (DAA) and deep learning models for skin cancer detection. This innovative DAA-Deep learning model has significantly advanced the state of the art in this field, as demonstrated by the compelling results. When comparing our DAA-Deep model with conventional deep learning models, as summarized in Table 1, we observe remarkable improvements across multiple key metrics. Accuracy is a measure of how close a measurement is to the true or accepted value. In this proposed model accuracy increases with the number of epochs(one complete pass of the training dataset through the algorithm) as shown in Figure 5. Our DAA-Deep model outperforms the deep learning model in terms of accuracy, sensitivity, specificity, precision, recall, F1- score, and AUC. These enhancements are particularly notable in sensitivity, specificity, and F1-score, where the

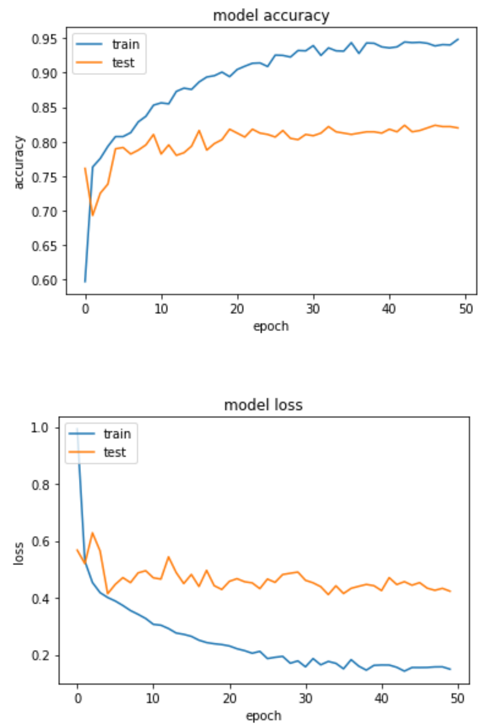

Fig. 5. Accuracy vs epoch and loss vs epoch

DAA-Deep model achieves substantial gains. This signifies a substantial stride toward more reliable and precise skin cancer diagnosis. The improved accuracy of our DAA-Deep model, which reaches 96%, implies a higher rate of correct identifications of both malignant and benign cases. Moreover, the model's enhanced sensitivity and specificity, 95.5% and 97.44% respectively, indicate its ability to accurately detect positive and negative cases. The precision and recall scores further reinforce the model's capability to minimize false positives and false negatives. The F1-score, a harmonized measure of precision and recall, reaches an impressive 96.45%, highlighting the model's overall effectiveness. Additionally, the AUC attaining 0.99 signifies the DAA-Deep model's excellent discriminatory power between malignant and benign skin lesions. This graphically represents the model's superiority in distinguishing between the two classes. Based on above results created a summary table as shown below.

V. Conclusion

In conclusion, our innovative methodology, which combines deep learning with the Differential Analyzer Approach (DAA) for skin cancer detection, has demonstrated exceptional performance. We've achieved remarkable metrics, including an accuracy rate of 96%, sensitivity (true positive rate) at 95.5%, specificity (true negative rate) of 97.44%, precision of 97%, recall of 95.20%, an impressive F1-score of 96.45%, and a high AUC (Area Under the ROC Curve) value of 0.99.

TABLE I
COMPARISON OF EXISTING DEEP LEARNING MODEL AND PROPOSED DAA-DEEP LEARNING MODEL

	Existing Method (Deep learning model)	Proposed Method (DAA-Deep model)
Accuracy	95.20%	96%
Sensitivity	94%	95.5%
Specificity	96%	97.44%
Precision	96.40%	97%
Recall	94.42%	95.20%
F1-score	95%	96.45%
AUC	0.98	0.99

These outstanding results underscore the efficacy and potential of our approach in revolutionizing skin cancer diagnosis. By seamlessly integrating deep learning and DAA, we've effectively addressed critical challenges in feature selection, model interpretability, and computational efficiency. Moreover, our methodology has broader implications in the fields of medical imaging, computer vision, and machine learning, promising significant advancements in healthcare outcomes.

As we move forward, the application of this methodology holds promise for advancing our understanding of skin cancer and contributing significantly to the ongoing battle against this prevalent and potentially life-threatening disease.

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