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Enhancing the Diagnosis of Skin Cancer Using Active Learning and Transfer Learning Techniques

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ABSTRACT

Nowadays, skin cancer is regarded as one of the deadliest cancers that people can get. Skin cancer can be either benign or malignant, with melanoma being the most surprising of the two types. They include basal and melanoma. The topic of Sustainable Development Goal (SDG) 3: "Good Health and Well-Being" is relevant to this work. In particular, the goal of this manuscript is to lower the early mortality rate from non-communicable diseases (NCDs), such as cancer, by one-third through treatment and prevention. Treatment for melanoma cancer may benefit from early detection. Numerous systems in use today attest to the significant role that computer vision may play in medical image diagnosis. In this work, an offer methodology for classifying medical photos into benign or malignant tumors using machine learning is proposed. First, we organize and process the image data, and then we train and evaluate the model. The first step of the process is to collect image data from pre-made folders that have been separated into training and testing sets, as well as benign and malignant categories. File paths are combined into data frames for each category and set, which are subsequently labeled appropriately. Active Learning V3 + approach was employed at the inception.

1. Introduction

The quality of life is greatly impacted by cancer, which is one of the main causes of mortality globally and is brought on by skin exposure to UV radiation from the sun. Early and precise diagnosis is essential for enhancing treatment results and survival rates [1]. The shortcomings and difficulties of conventional cancer diagnostic techniques may be addressed by deep learning, opening up new avenues to improve cancer detection's precision, effectiveness, and accessibility [2] [3]. One of the top sectors using computer vision technologies is healthcare. Notably, medical image analysis produces organ and tissue visualizations to aid in prompt and precise diagnosis by medical professionals, improving treatment outcomes and life expectancy. This is especially true in the medical field when it comes to identifying skin cancer by examining moles, skin lesions, etc. Computer vision and learning algorithms play a major role in human disease diagnosis and detection. [4] [5] Learning methods known as Convolutional Neural Networks (CNNs) have become increasingly popular in contemporary computer vision applications. This is due to the fact that CNNs are more adept at making predictions and have the propensity to favor larger networks with more intricate memory and processing needs. [6] [7] [8] To increase the precision and effectiveness of skin cancer diagnosis while lowering the need for invasive biopsy procedures, a novel deep learning model was created utilizing transfer learning and data augmentation approaches. [9] [10]

Melanoma and non-melanoma skin cancer are the two primary classifications for melanomas. Malignant melanomas are more common in the skin than in the mouth, intestines, or eyes. Melanoma development is influenced by both genetic and environmental factors. [11] [12]. An image-based AI method more especially, the EfficientNet-B0 architecture has been suggested to classify monkeypox from pictures of skin lesions. Exposure to the virus causes monkeypox. A person can contract the virus by touching a contaminated object or by coming into close contact with an infected human or animal person [13]. Modern technologies including machine learning (ML), deep learning (DL), and image processing techniques have combined to greatly improve the diagnosis and classification of skin cancer in recent years. [14] Using CNN and ViT models in combination with XAI approaches applied to the model improved the classification accuracy and consistency of skin cancer. Furthermore, the deep learning models' decision-making procedure was made more open. [15] Melanoma, squamous cell carcinoma, and basal cell carcinoma are the three primary forms of skin cancer. Your risk of developing skin cancer can be decreased by limiting or completely avoiding ultraviolet (UV) radiation exposure. You can detect skin cancer early by keeping an eye out for strange changes in your skin. The secret to successfully treating skin cancer is early detection. [16] Data analytics in the healthcare industry refers to the process of gathering, analysing, and interpreting vast amounts of healthcare data in order to drive decision-making and derive insightful information. Enhancing organisational performance, operational efficacy, and patient care are the goals of this procedure. Analysing healthcare data for patterns, trends, correlations, and linkages requires the use of sophisticated statistical techniques, machine learning algorithms, and data visualisation tools. Approximately 10 million people died from skin cancer worldwide in 2020. According to estimates from the World Health Organisation, one-third of all cancer diagnoses globally are for skin cancer. The United States reports more than 5.4 million new instances of skin cancer annually, making it a global public health concern. [17] [18] [19] Accurately identifying key regions using a deep-architecture CNN can be challenging. A vision transformer (ViT) model, which views each block as a distinct entity and is capable of learning high-quality intermediate representations from vast volumes of data, was employed to mitigate this issue. [20] [21] [22]. In the fields of medical imaging, disease diagnosis through examinations, and condition prediction, deep learning has demonstrated encouraging results. This results in more precise diagnoses and individualized treatment programs by automating the processing of complicated medical data. [23].

Using the naked eye to diagnose skin cancer is very subjective and rarely generalizable. Reward tables are used in reinforcement learning to incorporate human criteria into the AI system. These are instruments that include the results of clinical evaluations, both favorable and negative, from the viewpoints of the patient and the doctor in the decision-making process. Through the analysis of medical images, a deep learning-based algorithm is presented that can rapidly detect, identify, and classify skin diseases; it can also be used to categorise a range of benign and malignant skin lesions into distinct groups, assisting patients in receiving the appropriate medical care. [24] [25]

2. Literature Review

K. Ali, Z.A. Shaikh, A.A. Khan, et al. [1]. showed that a pipeline for image preprocessing was developed to detect skin cancer. Hairs were eliminated, the dataset was supplemented, and the photos were resized to meet each model's specifications.

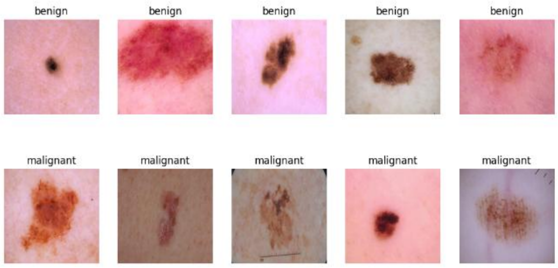

Fig. 1. Sample of the skin cases.

The HAM10000 dataset was used to train the EfficientNets B0-B7 models through fine-tuning Convolutional Neural Networks and transfer learning with pretrained ImageNet weights. S Jinnai, N Yamazaki, et al. [26] They recommended detecting skin cancer with this investigation. A total of 3551 patients had 5846 clinical images of benign or malignant pigmented skin lesions. Among the pigmented skin lesions were malignant (malignant melanoma and basal cell carcinoma) and benign (nevus, seborrhoeic keratosis, senile lentigo, and hematoma/hemangioma) tumours. A test dataset was created by randomly selecting 666 patients, with one photo selected for each participant. To create the training dataset, the remaining 4732 images which included 2885 patients were given bounding-box annotations. Following the development of a faster, region-based CNN (FRCNN) using the training dataset, the model's performance was evaluated on the test dataset.

Satin Jain, Udit Singhania, et al. [2] suggested that the HAM10000 dataset be used in this study to compare six distinct transfer learning networks for multiclass skin cancer classification. To account for the imbalance in the dataset, we duplicated pictures from low-frequency classes. VGG19, InceptionV3, InceptionResNetV2, ResNet50, Exception, and Mobile Net are among the transfer learning networks that were assessed in this investigation. With few false negatives, high F-measure scores, and accurate classifications, the results show that picture replication works well for this task. With an accuracy of 90.48 and the best recall, precision, and F-measure values among the transfer learning networks analysed in this study, the results demonstrate that Exception Net outperforms the others.

Taher M. Ghazal, Sajid Hussain, et al. [27] proposed using a specially pretrained Deep Convolutional Neural Network (DCNN) in this system. The last layers of the pre-trained Alex Net model are modified to address the specific problem. The SoftMax layer is altered in order to identify binary categorisation. The proposed model is fully trained on a dataset of 1,920 images of skin malignancies, with 960 images for each class of benign and malignant tumours. After training is complete, the model is compared to a set of 480 images, 240 for each class. The proposed model is assessed using the following metrics: accuracy, sensitivity, specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV), False Positive Rate (FPR), False Negative Rate (FNR), Positive Likelihood Ratio (PLR), and Negative Likelihood Ratio (NLR). At an accuracy of 87.1%, the proposed model performs better than conventional classification methods.

Ansari, Uzma Bano, and Tanuja Sarode. [28] For the early detection of skin cancer, they have released an SVM-based method. It helps patients more. Image processing techniques and the Support Vector Machine (SVM) algorithm are employed in the diagnosing process. To enhance the skin cancer dermoscopy image and eliminate noise, a number of preprocessing procedures are used. We then use the threshold approach to segment the image. Certain features in the image can only be extracted with the use of GLCM technology. Classifiers are supplied these properties. They use support vector machines (SVM) to achieve categorisation. It categorises the supplied image as either benign or malignant.

Hardik Nahata and Satya P. Singh. [29] In order to facilitate early diagnosis, the project proposal states that the objective is to create a convolutional neural network (CNN) model that can identify and categorise different types of skin cancer. With Keras and TensorFlow as the backend, Python will be utilised to develop the CNN classification model. Convolutional, dropout, pooling, and dense layers are among the types of layers that can be employed in the training process to develop and evaluate various network topologies. Additionally, the model will employ transfer learning techniques to achieve faster convergence. To train and assess the model, a dataset from the International Skin Imaging Collaboration (ISIC) challenge archives will be used.

Pratik Dubal, Sankirtan Bhatt, et al. [30] They suggest that this study detects and classifies skin lesions as either benign or malignant using images captured by standard cameras. Following image segmentation and feature extraction using the ABCD rule, a neural network is trained for accurate lesion categorisation. 76.9% of the 463 pictures were correctly sorted into six classes by the trained neural network.

Shivangi Jain, Vandana Jagtap, et al. [31] An image processing-based computer-aided approach for identifying melanoma skin cancer is described in this study. The technology uses state-of-the-art image processing algorithms to evaluate the skin lesion image and identify whether skin cancer is present. In order to segment and feature the images, the lesion image analysis tools use texture, size, and shape analysis to check for a variety of melanoma traits, such as asymmetry, border, colour, diameter (ABCD), etc. Both normal skin and melanoma cancer lesions are identified in the image based on the obtained feature characteristics.

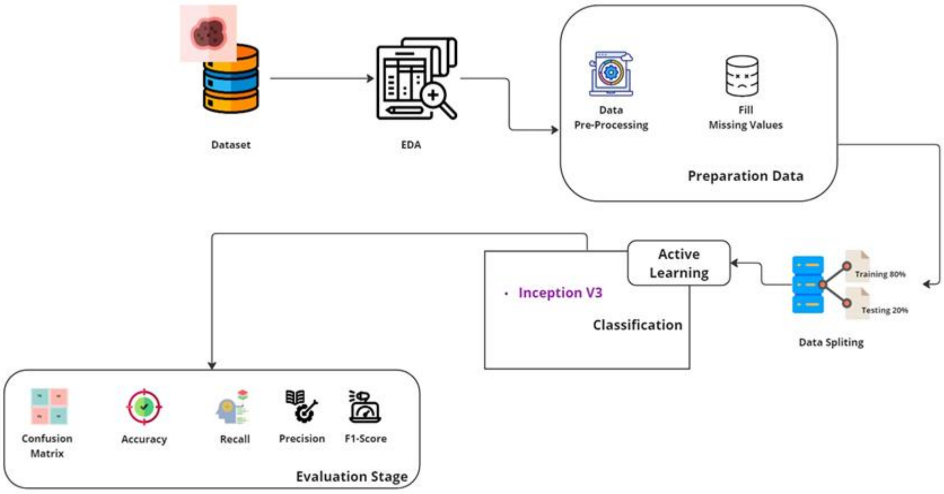

Fig. 2. System architecture.

Mahmudul Hasan, Surajit Das Barman, et al. [32] This study suggested a machine learning and image processing-based artificial skin cancer diagnostic technique. [33], [34]. Following the segmentation of the thermoscopic pictures, the feature extraction technique is used to extract the characteristics of the damaged skin cells.[35]. The retrieved features are stratified using a convolutional neural network classifier that is based on deep learning. [36], [37].

3. Proposed Sysetem

The method used to detect image data relies on extracting certain features from images to determine whether they contain data related to malignant or benign skin cancer. The features are then classified to decide whether or not they are malignant or benign. The core of the methodology is training a machine learning model using a transfer learning approach with the InceptionV3 architecture. Figure 1 below shows some examples of malignant or benign cases.

3.1. System flow diagram

The proposed architecture consists of multiple stages as follows:

- Data set: population data that contains solutions
- Pretest process: neglect any unwanted range
- Preparation: data be ready to use
- Classification: test the type of data
- Destino making: final report for data set

All the parts were fixed in Figure 2 below, which describes the overall proposed work.

4. Methodology

The methodology described involves organizing and processing image data, followed by training and evaluating a machine-learning model for the classification of medical images into benign or malignant tumors. Initially, the process starts by gathering image data from predefined folders that segregate images into training and testing sets, further divided into benign and malignant categories. For each category and set, file paths are consolidated into data frames, which are then labeled accordingly. Following the data organization, exploratory data analysis (EDA) is conducted to understand the distribution of the classes across the training and testing sets. This includes generating visual representations like bar and pie charts to visualize the proportion of benign and malignant images, ensuring there is balance, or noting any imbalance that could affect model training. The preprocessing step includes augmenting the images by applying rotations, thereby artificially increasing the dataset size and variety, which is crucial for training robust models. Images are then normalized to scale the pixel values, facilitating more stable and faster model training.

The core of the methodology is training a machine learning model using a transfer learning approach with the InceptionV3 architecture. Initially, the base model's weights are frozen to leverage learned features without altering them during the first training phase.

Table 1. classification types

Class	Precision	Recall	F1-score
0	0.90	0.91	0.90
1	0.88	0.87	0.88

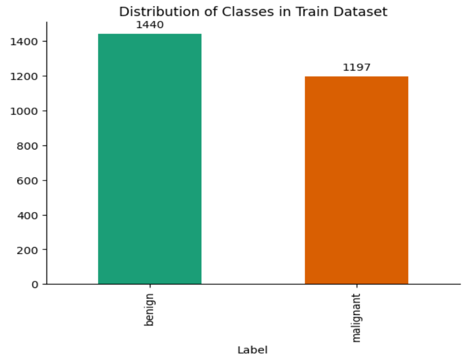

Fig. 3. Populations in two classes with given No. Iteration.

The model is extended by adding new layers to tailor it to the specific task of tumor classification. This setup is first trained on an initial subset of the data. Active learning is incorporated as a dynamic part of the training process, where the model iteratively queries the most uncertain samples from an unlabeled pool of data.

This method is aimed at efficiently using data and refining the model by focusing on samples from which it can learn the most at each iteration. Standard measures like accuracy, precision, recall, and F1-score are used to assess the model. Confusion matrices and classification reports are also used to provide comprehensive information about the model's performance across several classes. Training history visualisations allow to understand the model's learning trajectory and make appropriate adjustments by displaying the evolution of the model's accuracy and loss over epochs. In order to efficiently identify medical images—a critical function in aiding diagnostic procedures—the methodology combines methodical data processing, advanced model training with active learning, and thorough evaluation.

By carefully selecting the most instructive data points, the machine learning method known as "active learning" enhances model performance. Active Learning enhances efficiency, improves model correctness, and decreases the requirement for a lot of labelled data by actively querying the most ambiguous or instructive samples.

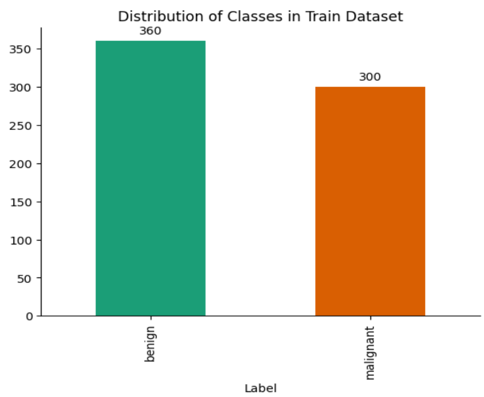

Fig. 4. Populations in two classes in other train processes and No. Iteration.

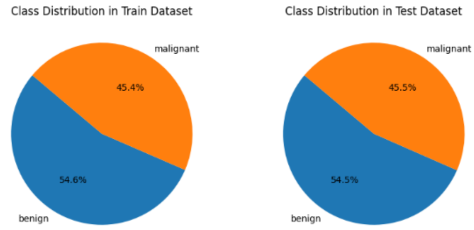

Fig. 5. Train and test percentage of distribution.

This method has been effectively used in a number of fields, such as recommender systems, natural language processing, and picture classification.

5. Results

The model's ability to differentiate between benign and malignant tumours with a high degree of accuracy is highlighted in the classification report. The model obtained a precision of 0.90 and a recall of 0.91 for benign tumours (class 0), yielding an F1-score of 0.90. Likewise, with an F1-score of 0.88, the model demonstrated a precision of 0.88 and a recall of 0.87 for malignant tumours (class 1). The model's overall accuracy in both categories was 89%, indicating that it was successful in categorising the medical photos.

This degree of precision indicates that the model is dependable in its forecasts, which makes it a valuable instrument in medical diagnostics where differentiating between benign and malignant tumours is essential.

The data that are collected has two classes to simplify the recognition, and by using the training process by the proposed method, the two classes were reached, as shown in figures 3-4 below. Figure 5 shows the train and test percentage of distribution according to the iteration number. The positive and negative classes, as shown in Figure 6, describe the total amount of solution.

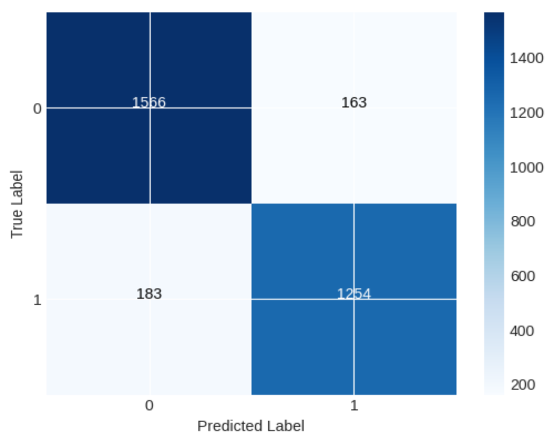

Fig. 6. Positive and negative classes

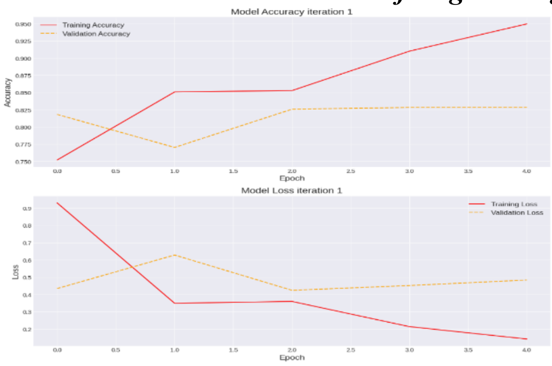

Fig. 7. Accuracy and loss for the proposed work.

1. **True Positives (TP)** - 1254: In these instances, the positive class (label 1) was accurately predicted by the model.
2. **True Negatives (TN)** - 1556: The negative class (label 0) was accurately predicted by the model in these instances.
3. **False Positives (FP)** - 163: In these cases, the model predicted the positive class (label 1) which was really negative (label 0).
4. **False Negatives (FN)** - 183: In these cases, the model predicted the negative class (label 0) accurately, but the actual class was positive (label 1).

6. Performance Metrics

From these values, we can calculate key metrics:

• Accuracy: (TP+TN)/(TP+TN+FP+FN)
• Precision (for positive class): TP/(TP+FP)
• Recall (for positive class): TP/(TP+FN)
• F1 Score: 2× (Precision× Recall / Precision+ Recall)

When training machine learning models, especially with neural networks, accuracy and loss often fluctuate as the number of training iterations (or epochs) changes. Here's an overview of why this happens and what factors contribute to these changes:

- During training, the model updates its parameters with each iteration to minimize a predefined loss function.

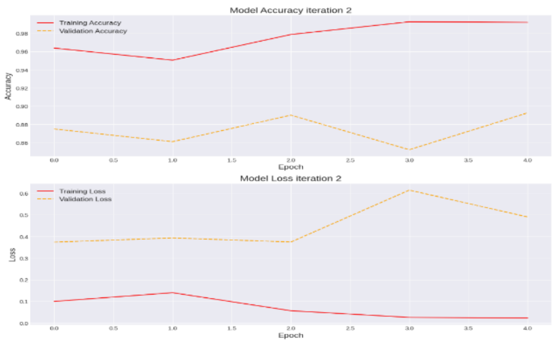

Fig. 8. Accuracy and loss for the proposed work for another iteration.

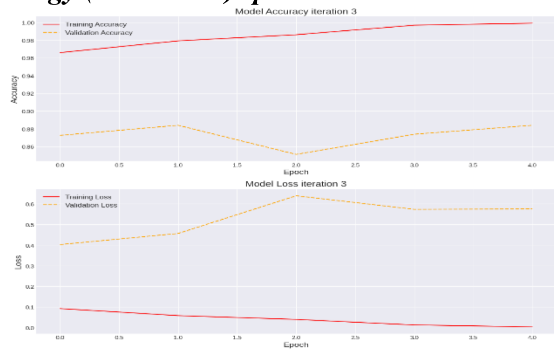

Fig. 9. Accuracy and loss for the proposed work for another iteration.

As iterations increase, the model's training loss usually decreases, indicating it's learning to fit the training data better.

- In the beginning, large improvements in accuracy and loss are common. However, after many iterations, improvements can become smaller as the model approaches convergence—where further learning may result in only marginal gains.
- The learning rate determines the step size during optimization. A high learning rate can lead to faster convergence but may cause the model to overshoot optimal solutions, especially if training continues for too many iterations.
- A lower learning rate requires more iterations to achieve the same level of accuracy or loss, but it may allow the model to settle more precisely in the minimum of the loss function.
- Loss and accuracy do not always change proportionally. For example, a model may reduce its loss by making small adjustments that don't always lead to changes in accuracy, especially as it gets closer to convergence.
- In classification, accuracy is a discrete measure (correct or incorrect prediction), while loss provides a continuous measure of the model's confidence in its predictions. Thus, loss might continue to improve even when accuracy appears to stabilize.
- Techniques like early stopping monitor validation loss during training and stop the process if performance on the validation set starts to worsen, preventing overfitting.

Table 2. The difference between proposed and other ones.

Ref	Method	Accuracy
[1]	EfficientNet B4	87.8%
[2]	FRCNN	88.50%
[3]	MobileNet	88.57%
Proposed Work	Inception V3 + Active Learning	89.07%

- Regularization methods (e.g., dropout, L2 regularization) can help the model generalize better, allowing for more iterations without overfitting, which can lead to improved accuracy.

Increasing or decreasing the number of iterations has a direct impact on the model's ability to learn from the training data, balance generalization, and prevent overfitting. Finding the optimal number of iterations (or epochs) involves experimentation and monitoring both training and validation performance to strike a balance between - underfitting and overfitting. See Figures 7-9.

The comparison of different methodologies for classifying medical images reveals that the proposed work, which utilizes Inception V3 combined with active learning, achieves an accuracy of 89.07%. This performance slightly surpasses other methods reported in the literature. For instance, EfficientNet B4, noted in reference [1], reached an accuracy of 87.8%, while FRCNN and MobileNet, as mentioned in references [2] and [3], achieved accuracies of 88.50% and 88.57%, respectively. The incremental improvement in accuracy with the proposed method underscores the effectiveness of integrating Inception V3 architecture with an active learning approach, suggesting that this combination might be more adept at handling the intricacies of medical image classification.

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