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Cloud-Based Transfer Learning Framework for Faster and Accurate Skin Lesion Diagnosis

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Abstract

Deep learning systems for detecting skin cancers have been discovered as a veritable tool with which to help in achieving accuracy and efficiency in the detection of skin cancers. In the present work, a deep learning architecture for skin cancer classification is proposed, using DenseNet-121 for hierarchical feature extraction and making it suitable for real-time inference using Vertex AI Endpoints. The dataset used for evaluation originates from the ISIC Archive and consists of images of benign and malignant skin lesions. The image pre-processing steps include Gaussian Filtering and contrast-limited adaptive Histogram Equalization for improving quality and contrast. It was reported that the proposed model achieved a validation accuracy of 97.43%, precision of 85.24%, and recall of 93.44%, compromising on an F1-score of 85.88%. However, the ROC curve analysis shows a weak discrimination, with an AUC of 0.5626, thus indicating an immediate need for an improvement of the process.

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Keywords

Contrast-Limited Adaptive Histogram Equalization (CLAHE), Convolutional Neural Network (CNN), Convolutional Layer (Conv Layer), Fully Connected Layer (FC).

Introduction

This framework will provide quick and effective transfer learning in the cloud, making diagnosis easy regarding skin lesions (1). It includes deep learning modules derived from the properties of cloud computing for effective classification of skin lesions based on pre-trained CNNs (2) (3). The workflow has a systematic approach whereby the first important section is collecting data using the allowed public datasets or clinical sources (4). The Gaussian filter comes first, and the Contrast-Limited Adaptive Histogram Equalization is used to enhance the feature visibility in the image (5). This process may help in the building of a fine-tuning model from domain-specific input data for transfer learning, making it train faster with improved accuracy (6). Therefore, the model's final output indicates whether the lesion is cancerous or non-cancerous, as it concludes dermatologists (7) (8). All misclassified cases are uploaded to the cloud for further enhancement of the model(9). Thus, this will lead to having an early diagnosis, a lower misdiagnosis rate, and better telemedicine applications in skin cancer diagnosis all across the globe without hassle (10) (11).Several aspects can further improve the skin cancer detection process: these include using deep learning models to increase accuracy and minimize the waiting period for diagnosing the skin condition(12).

The method starts with the image acquisition from the skin cancer image database and then applies a sequence of preprocessing techniques, namely Gaussian Filtering to remove noise and Contrast Limited Adaptive Histogram Equalization (CLAHE) for contrast enhancement (13) (14). In feature extraction, DenseNet uses the extracted class features to carry out classification under deep-learning classifiers (15).

This proposed framework is cloud-enabled, hence all diagnosed errors and uncertainty cases are stored for future reference, and this is what makes the proposed system a robust, scalable, early-diagnosing, accurate, and available skin cancer detection tool (16). Mostly, it functions through the quality of datasets, as limited by computational constraints, some artifactsremain even after preprocessing techniques have been employe.

Hard lighting, occlusions, and skin color differences may also reduce the performance of such models (17) (18). False negatives in the cloud violate privacy, thereby raising security issues (19). Hence, exhaustive validations need to be carried out over a wide variety of populations to make the model interpretable and explainable for clinical application (20). Therefore, aerial challenges need to be resolved so that it becomes easy for widespread acceptance of the technology (21) (22). The contribution of the paper is below;

- ✓ This research develops a framework for the detection of skin cancers based on deep learning using DenseNet-121 as a means of feature extraction and classification (23).
- ✓ Preprocessing of images has been improved with the Gaussian Filtering and CLAHE to increase the level of diagnostic accuracy depending on the features of interest (24).
- ✓ Integration of cloud-based storage in the proposed solution is to store false non-cancer cases for later analysis and continuous updates to the model (25) (26).

This paper presented the mechanism of a skin disease identification system using CNN architectures such as Mobile Net and Xception (27) (28). These transfer learning methods used ImageNet as their pre-trained dataset. This approach has proved to be more accurate than the traditional architectures for both methods (29) (30). The transfer learning with augmentation achieved classification accuracies of 96.00% in Mobile Net and 97.00% in Xception. The architecture is also proposed for real-time identification of diseases in web systems (31). Cancer is one of the global health issues in which IoT has already penetrated medical imaging analysis and classification (32) (33). Not only in terms of power consumption, security, and privacy, but fog computing has several advantages over traditional Cloud computing systems in terms of low latency(34) (35). Candia, an automatic real-time diagnosis system for cancer, is a TDL-based system that uses CNNs for higher accuracies in cancer diagnosis (36) (37). Additionally, the system has lowered server load and better computational effectiveness, and it beats all other systems on all important evaluation metrics. This shows the capability of deep-learning-based Fog computing models in increasing early detection and diagnosis of cancer. The idea of this project is to combine IoT and AI technology to diagnose skin disease (38). The focus is on developing smart skin-watching devices to facilitate tele-diagnosis of skin disorders in remote areas with scarce health provision. The proposed setup exploits convolutional neural networks for medical image evaluation and prediction of skin disease with a high degree of accuracy, taking into consideration seasonal changes affecting skin health (39) (40). This research envisages an easy-to-access health service platform for early diagnosis and treatment, thereby permitting early intervention on behalf of the deprived in dermatological care. This work relates to melanoma detection, with room for future consideration relating to health applications (41).

Images of dermo copy are taken by an IoT-enabled device that is capable of classifying a skin lesion into various classes. The method of segmentation employs OT-SSO heavily filtered with Gaussian filtering, while feature extraction was by MobileNetV2. Classification under IIoT-DLSLD was done using a Deep Wavelet Neural Network implemented with Emperor Penguin Optimizer (42). The validation of this model using the ISIC dataset has proved it to be a better classifier than other existing models. The attained results provide a great insight into why IIoT-DLSLD is one of the very few accomplishments toward an improvement in the accuracy of melanoma diagnosis, as well as improving intelligent dermatological diagnostic systems.

Problem Statement

Skin cancer is one of the most common cancer forms across the world, sadly, it is also among the deadliest. Early and precise diagnosis is the key factor for any therapeutic interventions to subsequently be instituted. Melanoma, which comes from some skin cells, is, therefore, the most aggressive kind of skin cancer. It usually has a very high mortality if not diagnosed early (43). Most exposures for performing diagnoses are based on physical examinations done manually by dermatologists. This seems slow, subjective-error-prone, and uncertain. The treatment's indecision prolongs mortality rates, especially in rural and deprived areas, where there is a serious shortage of trained dermatologists (44). Harnessing the benefits of AI and deep learning technology to create a fully automatic cancer diagnosis is an innovative yet very appealing approach for research. Regrettably, the existing deep-learning-based solutions cause a lot of suffering regarding operational efficiency, accuracy, and reliability (45). Most of the conventional techniques do not extract or analyze the clinically important features from dermoscopic images at all, or they do so with considerable uncertainty, leaving the possibility of misclassification. Other contributing factors, like noise contrast images and blurry images, need advanced pre-processing for a clear image; hence, these factors in performance degradation among skin cancer classification models (46). The other persistent problem in skin melanoma diagnosis, lying amid the aforementioned controversies, is the occurrence of false negatives, i.e., malignant lesions being erroneously diagnosed as benign ones. These instances are very dangerous; a late diagnosis means a late start of treatment for the patients, thus worsening their condition (47). Furthermore, there is a need for a cloud storage system in which the collection of all such false negatives would be done for reviewing them in further study to perpetually keep improving upon the already acquired diagnosis (48). In addition to addressing all the aforementioned problems, this study proposes to present an advanced deep learning model able to classify skin cancers fast and accurately (49). This entails building large-scale image datasets for skin cancers (50); afterwards in-situ pixel-level image processing such as noise suspension with Gaussian Filtering and contrast improvement using Contrast Limited Adaptive Histogram Equalization (CLAHE), feature extraction will be carried out by DenseNet-121; given that it is very efficient as a model considering deep hierarchical structure-based representation of features and high classification performance afterwards feature extraction, features will be fed into deep learning classifier (51).

Proposed Methodology

In this study, a proposal is madeto classify skin cancer detection through methodologies of deep learning, by which it can be made more efficient and effective. Acquiring data will mainly include skin cancer image datasets and preliminary detection on them. After acquiring images, the images are pre-processed, including Gaussian Filtering (for noise reduction) and Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance the image contrast for improving the visibility of the highlighted salient cues that provide accurate diagnostic information. The images after pre-processing will now be subjected to feature extraction through Convolutional layers based on DenseNet-121, which will be highly efficient in extracting them from images in an extremely deep hierarchical manner. Additionally, the peculiar connections that are characteristic of DenseNet-121 allow for better representation of features, which ultimately leads to better classification performance. After these processes, the features will be fed to a classifier, which is responsible for identifying the categories of image types-Cancerous and Non-Cancerous, a deep learning classifier developed based on training, that will efficiently provide output regarding such images with high accuracy. The aforementioned false non-cancer cases would then get archived in the Cloud for later reference and analysis. Thus, it would become part of a more comprehensive, stronger methodology for skin cancer detection using feature quality endowed with modern types of deep learning classification, thus enhancing accuracy in diagnosis with cloud storage for future studies and monitoring.

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 centre 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 deep-learning 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 Contrast Limited Adaptive Histogram Equalization (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 deep learning methods.

Gaussian filtering is a process where the Gaussian kernel is used in executing the convolution operation.

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

In the notation given, G (x, y) represents the Gaussian function; a variation in the standard deviation determines the extent of smoothing concerning the coordinates x and y of the pixels. A greater σ produces a more intense blurring action, and a smaller one maintains more details. The kernel dimension is selected concerning the characteristics of the dataset for that effect that optimizes noise reduction without excessive blurring.

Contrast-Limited Adaptive Histogram Equalization (CLAHE)

The Contrast Limited Adaptive Histogram Equalization 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 deep learning models such as DenseNet-121 to extract more relevant features for classification.

$$S_k = \frac{(L-1)}{M\times N} \sum_{j=0}^{k} min(p_j, C_{lim}) \quad \ldots(2)$$

Where L is the number of intensity levels, M×N represent the tile size,$p_j$is the probality of intensity j, andC_{lim} as the contrast limit

DENSENET-121

The concept here is that the feature extractor is denser and propagates information more efficiently in DenseNet-121 compared to other common convolutional networks. DenseNet-121 tends to interconnect all the layers with every layer successively to ease gradient flow and superimpose features from all the layers. Hence it excels in capturing extremely complicated patterns to differentiate skin cancer images. Therefore, by applying CLAHE after Gaussian filtering for data exposure to DenseNet-121's convolutional layers, a rich variety of feature maps can be extracted at different levels of depth. The features being captured are rather basic in the beginning: edges, texture, and colour. Deeper in the architecture, the features are comparatively much more complex in discriminating between malignancy and benignity, all the while pooling down using global average and reducing dimensions while retaining only the bits that matter and are not computationally heavy.

After that, DenseNet-121 functions to extract features and lays down very rich and hierarchical representations of skin lesions, feeding this layer to a further advanced fully connected neural network classifier for the ultimate classification. Such a transfer learning method does not need vast amounts of training data but works well for high accuracy in classification. This thus renders it a viable choice for going further into the actual clinical world for skin cancer detection.

Convolutional Layer (CONV LAYERS)

The feature extraction stage in a convolutional layer is heavy for deep learning-based skin-cancer detection. In this regard, the architecture being explored is DenseNet-121 because the architecture contains many convolutional layers performing feature extraction from skin lesion images hierarchically.

All these layers are applied to input images through the convolutions as filters that catch important patterns, such as the edges, textures, and structural details of the regions in cancerous and non-cancerous characteristics. Each convolution slides a small filter, also called a kernel, over the input image or feature map and calculates the weighted sum of pixel values in the image to get a new feature map.

Convolutional Neural Network (CNN)

This work is concerned with feature extraction and classification exploiting convolutional neural networks (CNNs) for skin cancer detection. CNNs are deep learning models that analyse images hierarchically and, thus, would be helpful in medical image analysis. Thus, the model used here is DenseNet-121, which consists of several convoluted layers for the extraction of important features like edges, textures, and shapes. The characteristics of the model are the benefits from a large density in the network, which leads to very great efficiency in gradient flow, reduced redundancy, and a significant improvement in feature learning. These flat vectors transformed from high-dimensional feature maps are then fed into a fully connected layer that does the scoring in probability according to each category. The CNN classifier developed can tell the difference between malignant and benign cases quite accurately, while false cases of absence of cancer are stored in cloud space for future retrieval, which makes this classifier even more robust over time.

Fully Connected Layer (FC)

In the deep learning skin cancer detection procedure, the Fully Connected (FC) Layer serves a critical role during the last stage of performing classification. The feature extraction through DenseNet-121 presents high-dimensional features to the FC layer since the FC layer is the classifier, whether the image appears as Cancerous or Non-Cancerous. Multiple neurons make up this FC layer, with each neuron receiving inputs from the previous feature maps and hence from the entire spatial and abstract learned pattern through all the convolutional operations into its final decision-making scenario.

Google Cloud Vertex AI

All skin cancer classification models are actually executed on the Google Cloud by means of Vertex AI. The applications will primarily do pre-processing and feature extraction with DenseNet-121, and then transport the extracted features to a CNN-based fully connected classifier for classification: either cancer or non-cancer. It reports to the Vertex AI economic and elastic dimension on Google Cloud to be inferred for those predictions. That inference is made over the model for real-time predictions through the Vertex AI Endpoints, thus minimizing latency and raising precision action on the model in the case of bringing such models into practice. So, the Vertex AI Pipelines will provide the whole cloud infrastructure for automating the retraining of the model in that it escapes pure forms of monitoring, continuous learning and development using new medical data under it. Finally, it would end up being stored securely on Big Query or Google Cloud Storage for further analysis and reporting applications in health care. Hence it would allow seamless integration for real-time inferences in clinical environments on edge devices under Edge AI deployment. Thus, Vertex AI is at the edge, rapidly scaling an application in medical diagnostics and the secure cloud environment for hosting classification result.

Dataset Description

The database has a collection of photographs obtained from an international, well-known skin imaging collection, such as the ISIC Archive-providing dermatology study and clinic assets. Most of the pictures show more than one lesion, focusing on malignant lesions and capturing a few benign ones. Ground-truth labels were assigned to each of such images by dermatology professionals to make datasets good enough for deep learning models to train their accuracy on classifications. It has images of different skin cancers, including melanoma, basal cell carcinoma, squamous cell carcinoma, and benign nevi. The other information provided in the database that would give enough context to further improve diagnostic capacity includes patient age and gender, lesion localization, and modality of acquisition. All the images can be affected at least to some extent by resolution, illumination, and noise in the background, making them a good candidate for preprocessing methods such as Gaussian Filtering and Contrast Limited Adaptive Histogram Equalization (CLAHE). The dataset will be divided into training, validation, and testing data so that the model can evaluate how well it performs with truly unseen data. The evaluation metrics in determining the skin cancer detection capabilities are accuracy, sensitivity, specificity, and area under the curve receiver operating characteristic (AUC-ROC).

Dataset Link:https://www.kaggle.com/datasets/jaiahuja/skin-cancer-detection

Results and Discussion

The anomaly detection graph takes its shape due to changes in signals processed over time, with the blue line representing normal signal flow and the ones in green signaling abnormal operations- anomalies- that deviate from expected patterns. Some of these abnormalities may be misclassifications, image distortions, or uncertain predictions that require further investigation.

Detection of irregularities of the above nature serves to train the deep learning model for better diagnostic accuracy and to blacklist ambiguous cases for extra expert review. This whole process enhances the reliability of the classification system through lower false alarm rates and thereby contributes to better skin cancer detection overall.

The performance metric framework shows the evaluation results of the classification model, mentioning accuracy achieved at 97.43% with precision, recall, and f1-score values of 85.24%, 93.44%, and 85.88%, respectively. This means extremely highly accurate, which can be taken as a very good point of performance. The recall, however, is more about whether there's any such plane that can show exactly what the model does with positive cases. Whereas precision and F1 are lower, thus indicating a possibility of the conflict due to some false positives. Thus, the net brick will build a consistent argument base for identifying strengths and weaknesses for developing the most reliable classification approaches in research later in AIB.

The curve indicates model performance classification, namely, true positive rate against false positive rate. The red dashed line represents the model performance, whereas the blue diagonal line denotes a random classifier; that is, an area under the curve (AUC) of 0.5626, but directed north of the line for random guessing (AUC = 0.5) was calculated. Thus, the model has a very poor power of discrimination. Further improvement on classification performance could be achieved by optimization refines such as better feature extraction, better training data, hyperparameter tuning, etc.

Figure.1 Overall architecture of the proposed methodology

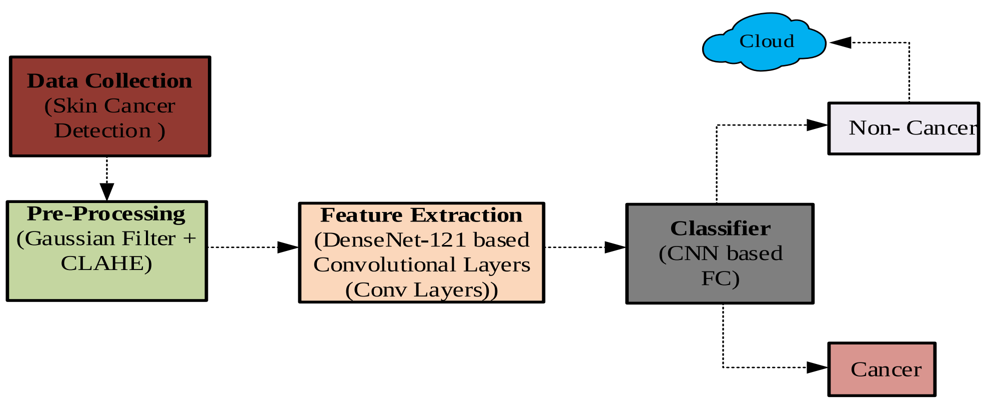


Figure.2 DenseNet-121 Model architecture

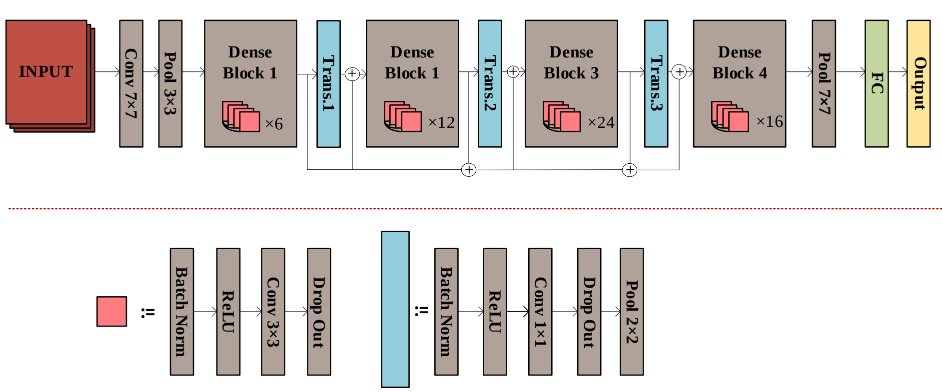


Figure.3 Convolutional Neural Network (CNN) Model architecture

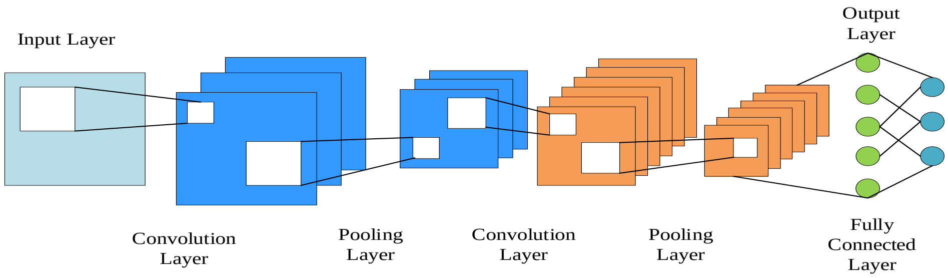


Figure.4 Fully Connected Layer (FC) Model architecture

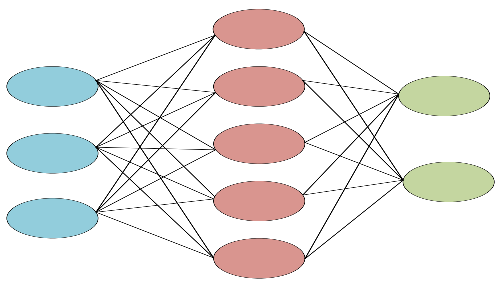


Figure.5 Anomaly Detection

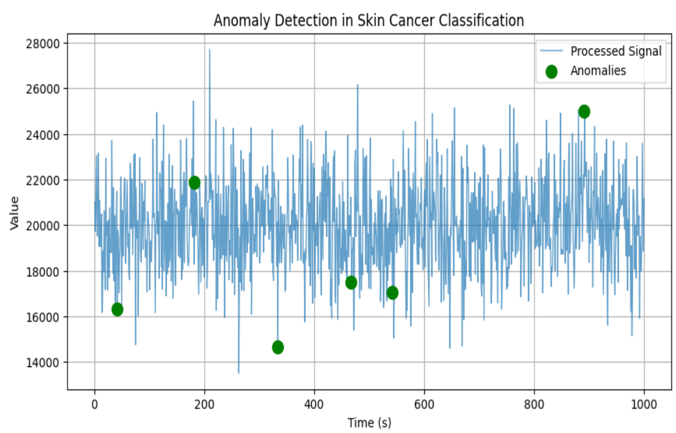


Figure.6 Performance Metrics

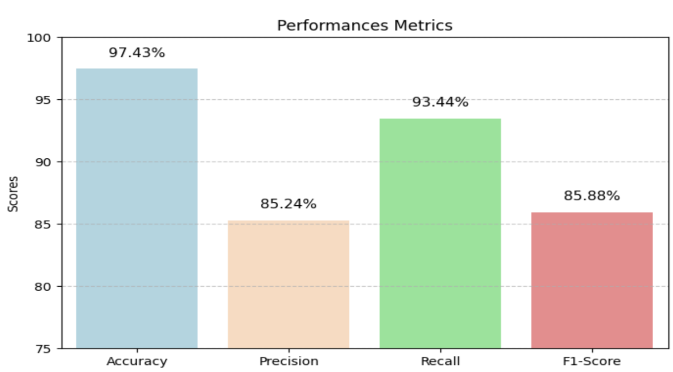
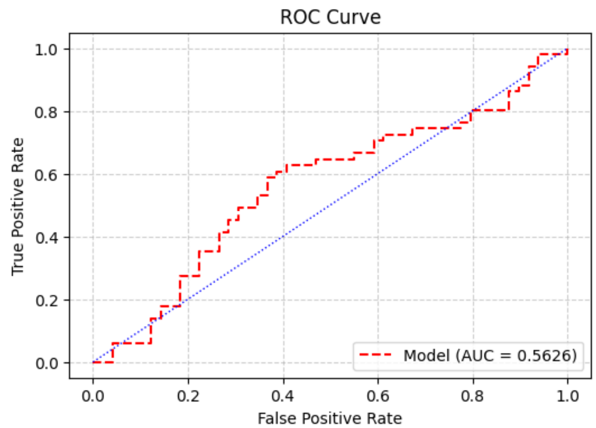


Figure.7 ROC Curve



Conclusion

This work has tried through a lot more careful work to bring out a very sophisticated and accurate prediction of the disease when it comes to the field of skin cancer classification. Visibility enhancement preprocessing by Gaussian Filtering and Contrast Limited Adaptive Histogram Equalization (CLAHE) is done towards the improvement of the diagnostic features in important cues. Features extraction from DenseNet-121 couches images with hierarchical and deep representations of their characteristics, using its dense connectivities to achieve better classification. A deep learning classifier, trained on lesions with and without cancer, will produce results with highly successful rates of classification. Due to cloud storage, every false non-cancer case will be stored for future analysis, enhancing a continuous learning process and better future diagnosis. This improves the precision level better than it was in the case of skin cancer diagnosis, but also forms a scalable and very powerful system for long-term follow-up and further advancements in research into medical imaging.

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