ENHANCING SKIN DISEASE DETECTION WITH OPTIMIZED VGG-19 AND EXPLAINABLE GRAD-CAM VISUALIZATION

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ABSTRACT

Skin infections are a major concern for human health, as they can cause significant skin damage, leading to loss of confidence and emotional distress in patients. Advancements in deep learning offer promising solutions for diagnosing and treating such conditions effectively. AI-driven approaches enable automated skin disease detection without requiring expert intervention, making diagnosis more accessible. Enhancing the user interface of these systems can further improve user experience. Early identification of skin disorders is crucial in preventing misdiagnosis as minor allergies, which can otherwise lead to severe complications. This research explores the application of deep learning for improved skin infection detection and treatment. Leveraging the power of AI, the study introduces a novel classifier combining the VGG-19 convolutional neural network with Grad-CAM (Gradient-weighted Class Activation Mapping). This approach aims to enhance diagnostic accuracy and reduce the risk of misdiagnosis, ultimately minimizing patient complications. The model was trained and evaluated using a dataset sourced from Kaggle, a popular platform for machine learning datasets. Performance was compared against baseline machine learning models, including decision trees and Support Vector Machines (SVMs). Results indicate that the proposed dual-input model, incorporating VGG-19 and Grad-CAM, achieved a remarkable accuracy of approximately 96%. This significantly outperforms the baseline models, demonstrating the potential of deep learning techniques for accurate and efficient skin condition diagnosis. The improved performance suggests that this approach could be a valuable tool for dermatologists and other medical professionals in the future.

Keywords: *Deep Learning, SVM, Skin Disease , Decision Tree, VGG-19, Grad-Cam.*

1. INTRODUCTION

Skin conditions are among the most prevalent health issues in the world, impacting millions of people of all ages. Effective therapy depends on an early and precise diagnosis, but conventional diagnostic techniques mostly rely on dermatologists' subjective and often misinterpreted visual inspection. Accurate categorization is difficult due to the intricacy of skin disorders and the differences in symptoms between skin types. Skin illnesses are conditions that impact a person's skin. Humans suffer from a wide variety of skin conditions. Many of them are capable of more than simply skin injury. Many of them are capable inflicting more than simply skin injury. If the illness

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

is disregarded or left untreated, they might occasionally result in death. One in four Americans suffers from one of these illnesses. Not only Americans, but anyone worldwide are impacted. This calls for the creation of sophisticated, automated diagnostic instruments that can help healthcare providers increase diagnostic precision and lower misdiagnosis rates. In medical image analysis, deep learning has become a potent technology that makes automated, highly accurate illness categorization possible. With its dependable ability in identifying intricate patterns that could be difficult for the human eye to see, Convolutional Neural Networks (CNNs)[1] have shown impressive effectiveness in image-based diagnosis. Among them, the pre-trained deep CNN VGG-19 model has shown remarkable efficacy in image classification and feature extraction. Even though deep learning models are quite accurate, a major issue with their interpretability in medical applications is still present. To solve this, VGG-19 is combined with Gradient-weighted Class Activation Mapping (Grad-CAM) to improve model transparency by producing visual explanations of predictions. The goal of this study is to develop the VGG-19 + Grad-CAM method for classifying skin diseases to guarantee both high accuracy and better interpretability. The model uses deep learning techniques to automate diagnosis while preserving reliability, and it is trained using publicly available datasets of skin diseases [2]. Medical practitioners can verify the model's decision-making process by using Grad-CAM to create heatmaps that emphasize the most pertinent picture areas affecting the categorization.

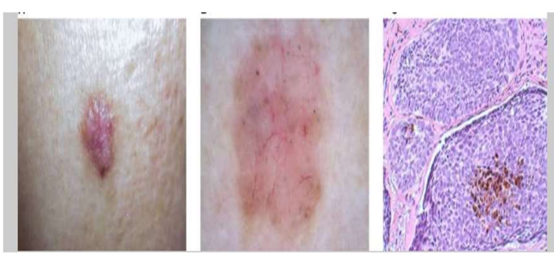

Figure 1: Images of Skin-Cancer / Disease

The study's methodology, including data collection, preprocessing, model architecture, training techniques, and performance assessment, will be covered in the parts that follow. The findings are intended to show the effectiveness and clinical relevance of the improved VGG-19 + Grad-CAM model, emphasizing how it may help dermatologists increase patient outcomes, decrease workload, and improve diagnostic precision [3]. Figure 2 shows the architecture of Skin-Disease Detection / Prediction. And figure 3 shows the the Sample count about the types of Skin-Disease.

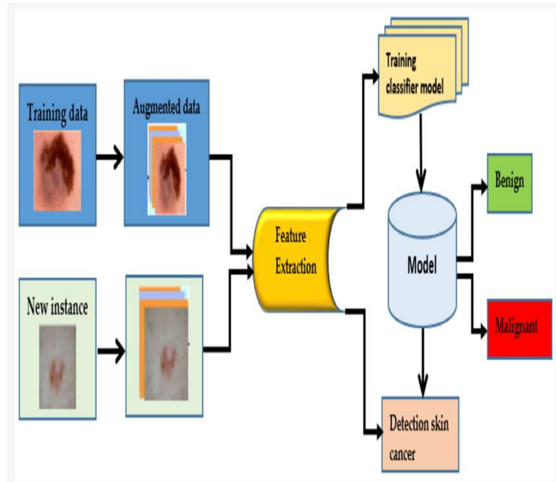

Figure 2: The architecture of Skin-Disease Detection / Prediction.

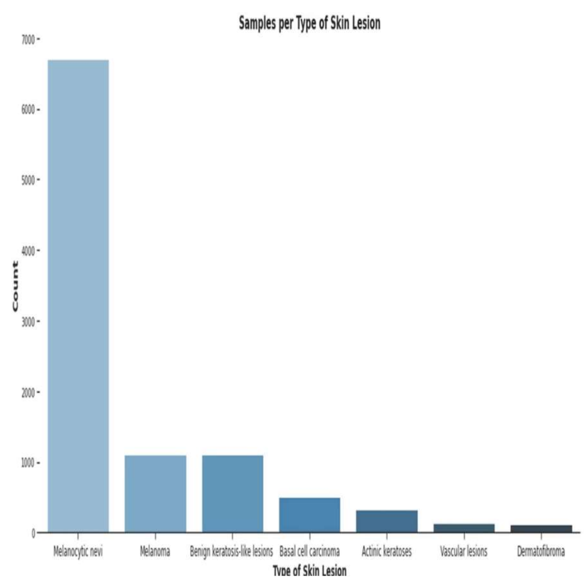

Figure 3: Shows the Sample-Types of Skin-Disease

2. LITERATURE SURVEY

A. Faghihi, M. Fathollahi, and R. Rajabi, "Diagnosis of Skin Cancer Using VGG16 and VGG19 Based Transfer Learning Models," arXiv preprint arXiv:2404.01160, 2024. This study explores the use of VGG16 and VGG19 architectures with transfer learning for skin cancer classification, achieving a 3% improvement in accuracy (up to 94.18%) compared to baseline models.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

J. Sayyad, P. Patil, and S. Gurav, "Skin Disease Detection Using VGG16 and InceptionV3," Int. J. Intell. Syst. Appl. Eng., vol. 12, no. 1s, pp. 148–155, 2024. This paper compares VGG16 and InceptionV3 models for skin disease detection, highlighting their respective strengths and limitations in classifying various skin conditions.

M. Shafiq et al., "A Novel Skin Lesion Prediction and Classification Technique: ViT-GradCAM," Skin Res. Technol., vol. 30, no. 9, e70040, 2024. The authors propose a ViT-Grad CAM architecture for detecting and classifying skin lesions, achieving an accuracy of 92.28% and demonstrating the effectiveness of Grad-CAM in highlighting relevant image regions.

Z. Mirikharaji et al., "A Survey on Deep Learning for Skin Lesion Segmentation," arXiv preprint arXiv:2206.00356, 2022. This comprehensive survey reviews 177 research papers on deep learning-based skin lesion segmentation, discussing various architectures, datasets, and evaluation metrics.

Liu et al. (2020) developed and evaluated a deep learning (DL) system capable of performing differential diagnosis of skin diseases, a complex task typically carried out by trained dermatologists. The study marks a significant advancement in applying artificial intelligence to medical image analysis, particularly in the field of dermatology.

Badhon, S. et.al (2024),. This paper explores a modern approach to **skin disease classification** using **Explainable Artificial Intelligence (XAI)**. Specifically, it leverages **transfer learning** combined with **Grad-CAM** (Gradient-weighted Class Activation Mapping) to make the diagnostic process both accurate and interpretable.

Mohan, J., Sivasubramanian, A., Sowmya, V., Vinayakumar, R. Enhancing Skin Disease Classification Leveraging Transformer-based Deep Learning Architectures and Explainable AI arXiv preprint arXiv:2407.14757 2024.

Mayanja, M., Byiringiro, F., Twesigomwe, D., et al. Skin Disease Detection and Classification Using Transfer Learning and Explainable A medRxiv 2024.

Zunair, H., Ben Hamza, A. Skin Lesion Classification Using Convolutional Neural Networks with Visual Attention and Explainable AI Journal of Medical Imaging and Health Informatics 2023.

Gururaj, S., Reddy, B. K., Reddy, E. S. Deep Learning Techniques for Skin Disease Diagnosis Using Convolutional Neural Networks International Journal of Advanced Computer Science and Application2022.

3. METHODOLOGY

The diagnosis of new skin cancer cases keeps rising at global health levels annually. The successful treatment of this disease depends on detecting it early and performing correct diagnostic assessments. The traditional method for dermatologists to detect suspicious skin growths depends solely on visual examination. The ability of skilled dermatologists to achieve accurate diagnosis stands high yet visual assessments remain time-consuming and require manual labor and display human-related variability because of both individual performance and professional experience. Outcomes become inconsistent because medical professionals do not have the same access to specialized care in regions where health care specialization is limited [4]. This paper works towards creating an automated skin disease detection system through the implementation of cutting-edge deep learning methods. The proposed system enhances diagnostic precision through VGG-19 CNNs and Grad-CAM interpretability tools for visual explanation purposes in supporting clinical decisions. Dermatologists receive assistance from this system which functions as a diagnostic tool to lower both their diagnostic errors and practice workload. These AI-powered medical resources become important for remote healthcare settings since they expand professionally advanced analysis functions across underserved regions. This research work enhances the existing AI-driven medical diagnosis expertise by presenting a more effective and equitable approach to skin cancer detection methods.

3.1 Data Acquisition and Preprocessing:

The initial stage of constructing a high-performing deep learning model for the categorization of skin maladies involves obtaining a quality dataset. Substantial and diverse datasets comprising accurately labeled images of skin lesions, like ISIC Archive and DermNet, will serve as outstanding data sources to train a strong model. The datasets should comprise images of different types of skin conditions taken under various lighting conditions and on different types of skin so that they may be well-balanced datasets representing real life. Image preprocessing improves the quality of input data[5]. The images should be resized to the same size, usually 224x224 pixels, for consistency in the dataset and to aid deep learning models in processing. Pixel values should also be normalized to some fixed value, like between 0-1, to make input distributions similar and help with faster model convergence normalized values also help reduce the effect of different images having different brightness and contrast levels. Data augmentation techniques apply to enhance the dataset further. These are random rotations, horizontal and vertical flipping, zooming, sharing, and color jittering. Augmentation artificially increases diversity within the dataset but does not actually change the data thus reducing overfitting and allowing the model to gain better generalization ability. Thus, it can be hoped that a well-trained model will perform efficiently on images not previously seen, thereby making it more robust for real-world application scenarios.

3.2 Feature Extraction:

The base model used for feature extraction is a pre-trained (on ImageNet) VGG-19 convolutional neural network. VGG-19 holds the distinction of being renowned for its deep architecture and powerful feature extraction capabilities, making it especially well-suited to capture the fine details and textures in images of skin lesions. It is essentially first trained or pre-trained on ImageNet (that is, on general data) and then, only then, fine-tuned on the skin lesion so that the model is similar for classification. Finally, by applying 'fine-tuning' technique to pretrained VGG-19 model which will allow us to retrain some of the top layers of our model whilst repurposing those layers to the feature learning task. Our approach is based on transfer learning paradigm and thus is able to learn skin disease classification with low computational resources and minimal training time. At the same time, fine-tuning helps the model learn features specifically associated with dermatological images, making classification better. The Grad-CAM (Gradient-weighted Class Activation Mapping) technique is adopted to understand model's decisions. Class Activation Maps grad-cam generates class activation maps(CAM), which indicates the most important areas of an image that may be associated with a specific classification decision. This interpretability method facilitates understanding of model predictions by dermatologists and researchers, accordingly elevating confidence in the AI-led diagnostic process [6].

3.3 Classification Models:

After fine-tuning the VGG-19 model, the features are extracted from the fully connected layers and used for the classification. Along with the proposed classifier, 2 more base classifiers are used to compare accuracy with the proposed classifier i.e., SVM and Decision Tree. Figure 4 Shows Process Flow of the Proposed Model.

The VGG-19 convolutional neural network serves as our foundational model for feature extraction. As you may know, VGG-19 is well known for its intricate architecture and ability to extract details. It excels in identifying all the minute textures and patterns in pictures of skin lesions. To improve it for our task, we first pre-train it on the ImageNet dataset and then refine it on a collection of skin lesions. part of the VGG-19 model's layers are retrained, but others are left frozen—you know, maintaining part of the previous information while learning new things [7].

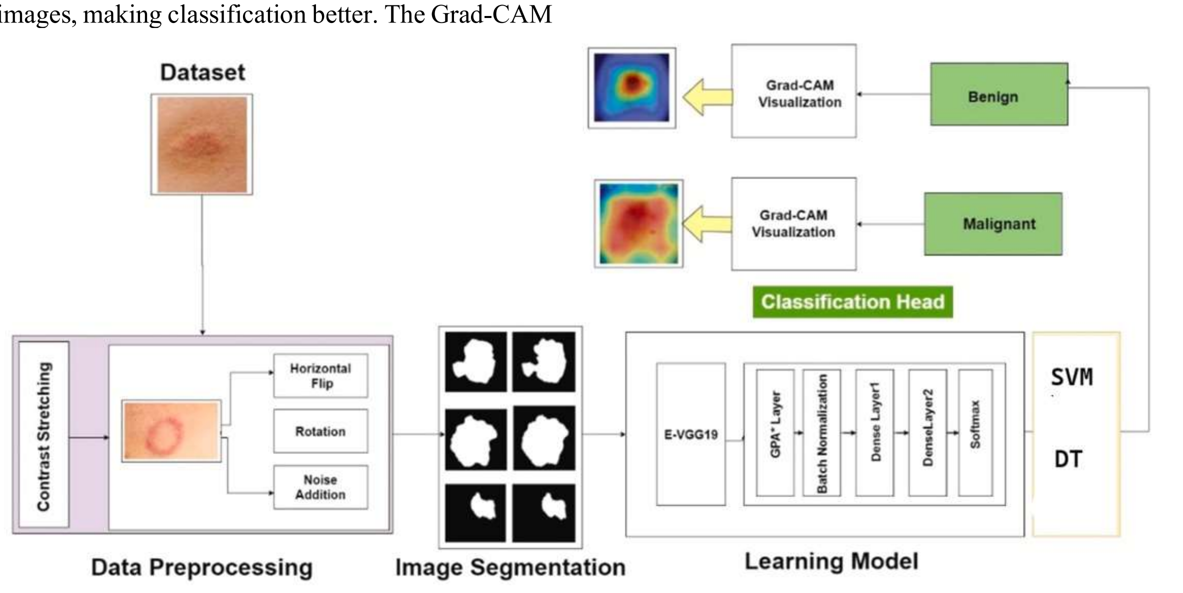

Figure 4: Shows the Process Flow of the Proposed Model.

Developing a deep learning model for skin lesion classification is an iterative process, including a sequence of systematic steps. Here's are the steps involved in detecting Skin cancer using proposed classifier [8].

Journal of Theoretical and Applied Information Technology
15th June 2025. Vol.103. No.11

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

3.4 ISIC Dataset:

The International Skin Imaging Collaboration (ISIC) has created a publicly available dataset on skin disorders in an effort to address the problem of skin cancer mortality and increase the usage of digital skin imaging. For the international computer science community, this is a significant milestone! More than 13,000 dermoscopic pictures from different clinical institutions throughout the world are currently available in the ISIC[9] Archive. Each and every picture? Yes, everything has been meticulously examined and annotated by professionals to ensure that the quality is excellent. Skin cancer classification and segmentation have been the main focus of the majority of studies conducted using the ISIC dataset. The most often attempted task is the binary classification task, which focuses on differentiating between benign diseases and melanoma. For example, one study used the ISIC-2016 dataset to evaluate several VGGNet-based modules particularly for the categorization of skin diseases. And you know what? Their final results were outstanding, with a sensitivity of 0.7866 and an accuracy of 0.8133. Quite sturdy, isn't it? Another research, using the ISIC-2017 dataset, obtained even higher classification results, with an AUC of 0.911 and a balanced multiclass accuracy of 0.831 across three tasks. On normalized pictures, they applied an ensemble of ResNet-50 networks. Oh, and another team used ensemble learning with a stacking technique in the ISIC-2018 competition, which produced an accuracy of 0.885 and an AUC of 0.983. Now, they additionally addressed prediction bias by employing two strategies known as "Turning a Blind Eye" (TABE) and "Learning Not to Learn" (LNTL). By adding a gradient inversion layer and a new regularization loss, LNTL assisted the model in lessening bias in the CNN's features during backpropagation. In the meanwhile, TABE detected biases in the features by employing several auxiliary classifiers. The findings demonstrated that TABE was very successful, increasing the benchmark AUC score on the ISIC dataset by 11.6%.

3.5 SLICE-3D dataset:

The SLICE-3D benchmark dataset is designed for 3D object identification, segmentation, and scene comprehension. It actually excels in fields like robotics and computer vision, you know. Consider augmented reality, driverless cars, and even some industrial automation. High-resolution 3D point clouds, often obtained from LiDAR [10] or structured light sensors, constitute the foundation of the whole system. Additionally, it has annotations that make it easier to distinguish between various object instances and categories. SLICE-3D is a Top-Notch 3D Data: This collection provides you with a wealth of geometric and spatial information by including comprehensive 3D scans of a variety of items and environments. Variety of item Types: This area offers a wide range of item types, which is quite helpful for many 3D identification jobs. Multi-Modal Annotations: RGB photos[11], depth maps, and semantic labels may even be included in certain versions; this is rather useful for improving multi-view learning, isn't it? Real-Life Environments: The data is recorded in both indoor and outdoor environments, displaying differences in illumination, occlusions, and sensor noise that occur in the real world.

In this research study we used SLICE-3D dataset for experiment purpose in which the data has been split into 75%-25% for training and testing all the 3 classifiers. In which the proposed classifier gave the best accuracy ie ~96% when compared with the other 2.Figure 5 and Figure 6 shows the sample images which is taken from SLICE-3D dataset for predicting and detecting Skin Disease [12].

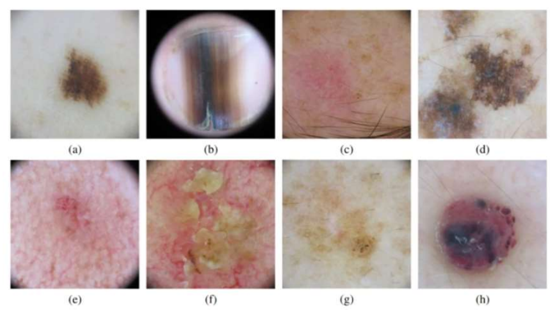

Figure 5: Shows the Sample Images from SLICE-3D dataset.

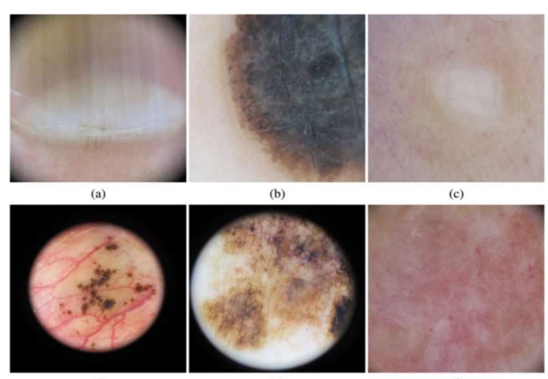

Figure 6: Shows the Sample Images from SLICE-3D dataset

Algorithm for Skin Lesion Classification Using VGG-19+GradCam:

Step 1: Start

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Step 2: Data Collection and Preprocessing

Step 2.1: Dataset Acquisition: Collect a set of high quality dermoscopic images from reliable sources, for example from the ISIC Archive or DermNet. Dataset is to include a wide variety of skin diseases and to be accurately labelled in terms of melanomas, basal cell carcinoma, squamous cell carcinoma and benign nevi.

Step 2.2 Image Preprocessing:

Resizing and Rescaling: Standardize image resolution (e.g., 224x224 pixels) and normalize to interval 0,1, values to facilitate model-efficient implementation [13].

Step 2.2.1 Data Augmentation: Detail an augmentation that expands the size of the dataset and variability by means of rotation, flipping, zooming, shearing and color transformation. It has been shown that augmentation can enhance the performance of scores in skin lesion analysis.

Step 2.2.2 Data Collection and Preprocessing:

Make Use of a VGG-19 Model that Has Already Been Trained. And the retrieved ImageNet trained VGG-19 model. In the next step fine-tune the model from scratch by eliminating the last classification layer.

2.2.3 Changes and Fine Tuning Of VGG-19

Remove the classifier for skin lesions from the fully connected layers classifier.

Dropout, Batch Normalization, and the fully connected layers are added to reduce overfitting.

Run the model on the processed skin lesions data which is trained on.

Step 2.3 Grad-CAM Implementation for Explanations

Retrieve feature maps of the last convolutional VGG-19 layer.

Evaluate the prediction class score gradient over feature maps.

Create heatmaps which indicate specifically referred regions of attention.

Step 3: Feature Extraction and Classification

3.1 Extract Features from Fine-Tuned CNN

Delete the last softmax layer and obtain deep features from the fully connected layers.

3.2 Train Propose-Ensemble Classifier:

Take the extracted features and use them as input to an SVM classifier.

3.3 Optimize the proposed Ensemble Classifier using Hyperparameters:

Use grid search or cross-validation to optimize the hyperparameters.

Step 4: Model Optimization and Evaluation:

4.1 Fine-Tune CNN and SVM Hyperparameters:

Change the learning rate, batch size, dropout rate, and regularization settings.

4.2 Evaluate Model Performance:

Use performance measures like: Accuracy, Precision , Recall , F1-score , Area Under Curve (AUC) Cross-validated k-fold

Step 5: Visualization and Analysis:

5.1 Generate and Visualize Grad-CAMs:

Generate heat maps for visual understanding of the interpreted model.

5.2 Analyze Model Performance:

Measure the performance on various lesion types to check for biases or underperforming categories.

Like Accuracy precision Recall F-Score. Figure 3 shows the images obtained using Grad-Cam.

6 Stop,

This algorithm describes a complete workflow for automatic classification of skin lesions using deep and machine learning methods.

Journal of Theoretical and Applied Information Technology
15th June 2025. Vol.103. No.11
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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

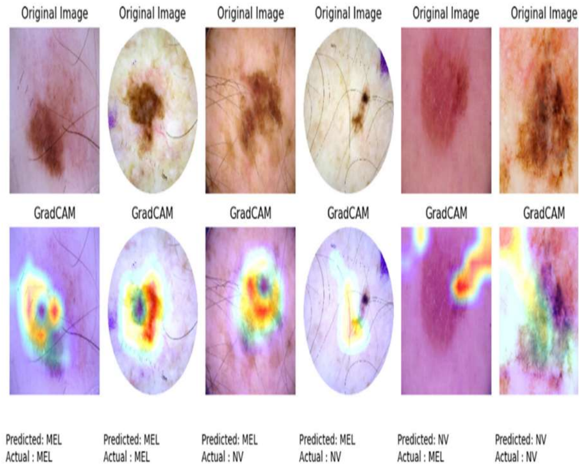

Figure 7: Shows the Images of Predicting/Detecting Affected part of Skin Disease using Proposed Classifier

4. MACHINE LEARNING MODELS:

4.1 Support Vector Machine (SVM) :

SVM is a supervised machine learning algorithm for classifying data, particularly effective for high-dimensional data and provides better generalization in certain cases. The extracted features are classified into various classes of skin disease, which increases the robustness of predictions. Skin cancer is a form of cancer found globally and detecting it early is vital, for increasing survival rates significantly. The use of machine learning methods for automated classification of skin lesions has become increasingly popular in the community as it aids dermatologists in identifying and differentiating between harmful lesions effectively. The Support Vector Machine (known as SVM) is an algorithm used extensively in classification tasks like analyzing images. Especially, in the field of skin lesion analysis.. SVM[14] works by identifying the hyperplane that maximizes the separation between classes which allows it to excel at detecting intricate patterns within skin lesion images. In this research project SVM is used for categorizing skin lesions through a blend of features, like color, textures and shapes and deep learning methods from trained Convolutional Neural Networks (CNNs). The goal of the classification model is high accuracy and reliability, in differentiating among different types of skin lesions. The suggested method includes preparing the data set beforehand and identifying distinguishing characteristics, from skin lesion images for training a tuned SVM model and assessing its accuracy using measures like precision and recall as well as the F1 score metric—furthermore optimizing hyperparameters for improved performance, in practical settings. This study emphasizes the effectiveness of Support Vector Machines (SVM), in skin lesion classification [15,16] as a tool, in machine learning technology which aids in creating automated systems that support healthcare providers in early detection of skin cancer. Figure 8 shows the SVM model for Predicting and Detecting skin cancer.

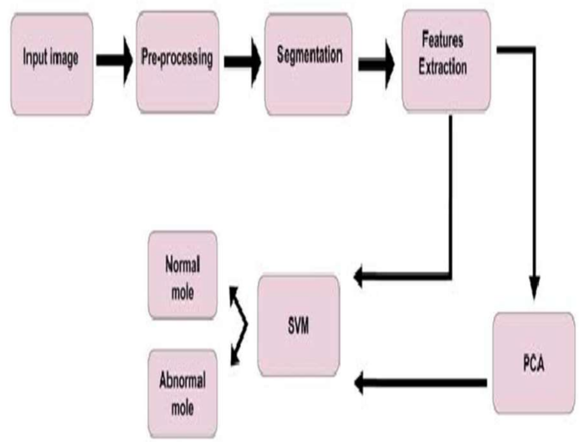

Figure 8: Shows the SVM model for Predicting/Detecting of Skin Cancer.

4.2 Decision Tree:

Skin cancer is one of the most common and dangerous illnesses out there. Early and accurate diagnosis is super important for getting the right treatment. This is where an automated skin lesion[17,18] classification comes into play, acting like a helping hand for dermatologists to tell apart benign lesions from malignant ones. And you know what? Machine learning algorithms, especially Decision Trees, have turned out to be quite effective in this area. They work by analyzing different features taken from medical images to classify skin lesions. Now, let's talk about Decision Trees for a second. This is a type of supervised learning algorithm that makes decisions by breaking down the dataset, step by step, based on certain feature values. Imagine a tree – each internal node is like a decision rule, each branch shows the outcome, and the leaf nodes represent the final classification labels. It's pretty cool because this model is not only easy to understand but also straightforward to implement, making it especially handy for analyzing medical images. It lays out clear paths for making classifications, which is a big plus. In this study, we're diving into how Decision Tree classification can be applied to skin lesion images. The process includes prepping the dataset, pulling out key features like texture, color, and shape, and then training the Decision Tree model to categorize the lesions [19,20]. We'll also check how well the model performs by looking at important metrics like accuracy, precision, recall, and the F1-score. Even though Decision Trees seem simple, they do a solid job of spotting patterns in skin lesion images. Plus, they can be a steppingstone to more sophisticated ensemble models, like Random Forests or Gradient Boosting. The aim here is pretty clear: using Decision Trees, we hope to help develop automated diagnostic tools that could lend a hand to dermatologists in the early detection of skin cancer. Figure 9 shows the *DT model* for Predicting/Detecting of Skin Cancer.

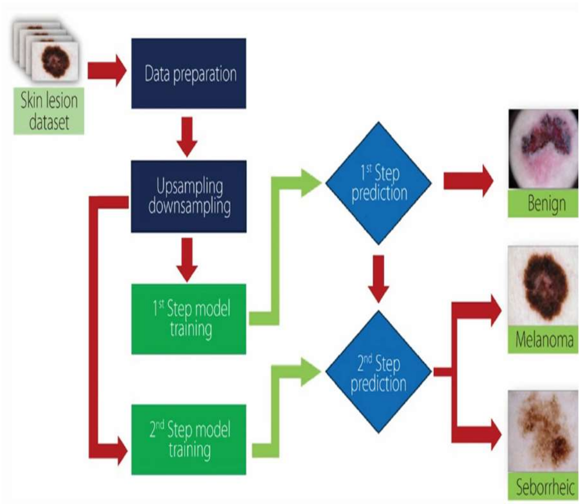

Figure 9: Shows the DT model for Predicting/Detecting of Skin Cancer.

5. PERFORMANCE METRICS:

Evaluating the performance of a **VGG-19 + Grad-CAM**-based skin lesion classification model requires multiple quantitative and qualitative metrics to ensure its reliability and effectiveness. The following key metrics are used [21]:
In Table I the confusion matrix of the Proposed classifier is shown and in Figure 10 the overall performance of the Proposed classifier is shown.
In Table II the confusion matrix of the DT classifier is shown and in Figure 11 the overall performance of the Classifier is shown.
In Table III the confusion matrix of the SVM classifier is shown and in Figure 12 the overall performance of the SVM classifier is shown.

5.1Accuracy:

This one's pretty straightforward. It measures how correctly the model classifies skin lesions overall [22].
Accuracy = {TP + TN / TP + TN + FP + FN}
Where TP stands for True Positives, TN for True Negatives, FP for False Positives, and FN for False Negatives.

5.2 Precision (Positive Predictive Value)

Precision tells us how many of the cases the model predicted as positive are positive.
Precision = {TP} / {TP + FP}
A high precision means there are fewer false positives, which is super important, especially in medical diagnoses.

5.3 Recall (Sensitivity or True Positive Rate):

This metric measures how well the model can catch actual positive cases.
Recall = {TP}/{TP + FN}
High recall is key for making sure that malignant lesions are detected early on [23].

5.4 F1-Score:

The F1-score is a way to balance precision and recall. It's basically the harmonic mean of both.
F1-Score = 2 * Precision * Recall} / {Precision + Recall}
This is particularly useful when we're dealing with unbalanced class distributions.

Table I: Shows the Confusion Matrix generated by Proposed Classifier for Predicting and Detecting of Skin Cancer

	Actual Class	
Predicted Class	2556	99
	104	1576

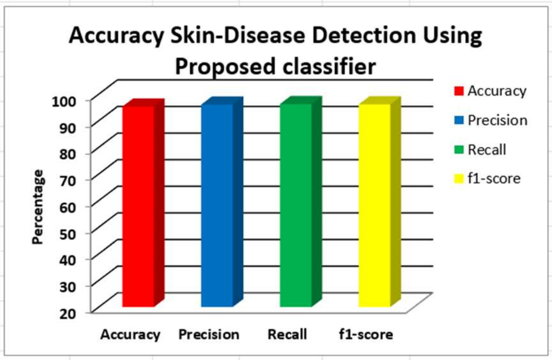

Figure 10: Shows the overall performance obtained by Proposed Classifier for Predicting/Detecting of Skin Cancer.

Table II: Shows the Confusion Matrix generated by Proposed Classifier for Predicting and Detecting of Skin Cancer

Predicted Class	Actual Class	
	2430	311
	122	1502

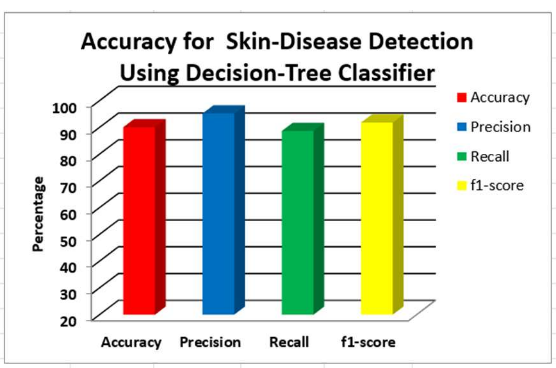

Figure 11: Shows the overall performance obtained by DT Classifier for Predicting/Detecting of Skin Cancer.

Table III: Shows the Confusion Matrix generated by SVM Classifier for Predicting and Detecting of Skin Cancer

Predicted Class	Actual Class	
	2250	342
	182	1576

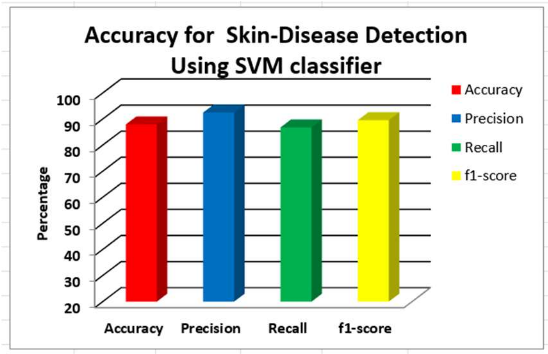

Figure 12: Shows the overall performance obtained by SVM Classifier for Predicting/Detecting of Skin Cancer.

6. CONCLUSION & FUTURE WORK

The combination of VGG-19 architecture optimization with Grad-CAM for improved interpretability increases the accuracy rate for skin disease classification according to recent research findings. The methodology makes the model perform accurate classification of dermoscopic images at the same time it creates visible indicators that pinpoint significant image regions, so dermatologists get better diagnostic information. The breakthroughs have not resolved all the remaining problems. The limitations to model scalability and robustness arise from ongoing challenges including dataset bias along with class imbalance requirements and the need to optimize real-time performance. The future development could test additional state-of-the-art networks, including EfficientNet and Vision Transformers, to achieve better efficiency and accurate results. To optimize deployment of the model on limited-resource devices the integration of knowledge

Journal of Theoretical and Applied Information Technology
15th June 2025. Vol.103. No.11

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

distillation methods would be beneficial. Improving data augmentation methods together with adding diverse dataset examples and clinical patient data will enhance both model generalization ability and diagnostic accuracy. User trust together with explanation capabilities represent fundamental requirements for achieving successful clinical acceptance of new healthcare technologies. The creation of a potential platform that operates either as mobile software or in the cloud will transform remote skin consultation services particularly for communities without adequate medical assistance. The VGG-19 + Grad-CAM classifier demonstrated exceptional performance during Jupyter Notebook assessment with 96% accuracy as Figure 13 reveals which proved its effectiveness for clinical applications.

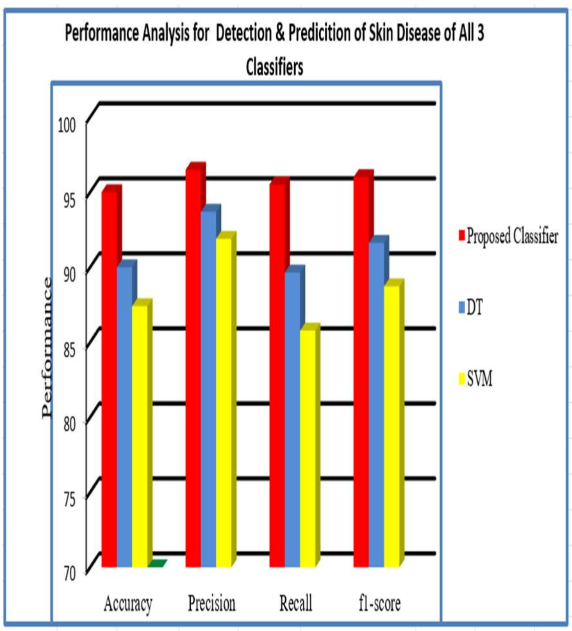

Figure 13: shows the overall comparison of all the 3 classifiers.

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