ENHANCED SKIN LESION SEGMENTATION AND CLASSIFICATION USING DEEP LEARNING AND OPTIMIZATION TECHNIQUES

A PROJECT REPORT

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BONA FIDE CERTIFICATE

Certified that this project report titled **ENHANCED SKIN LESION SEGMENTATION AND CLASSIFICATION USING DEEP LEARNING AND OPTIMIZATION TECHNIQUES** is the bonafide work of **ROHITH R (2023246038)** who carried out project work under my supervision. Certified further that to the best of my knowledge and belief, the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or an award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

This project represents an innovative approach to addressing the critical challenge of skin cancer detection and segmentation through the integration of advanced deep learning techniques and optimization algorithms. Given the severity of skin cancer as a leading health concern, timely and accurate diagnosis is essential for improving patient outcomes. However, the task of segmenting skin lesions, especially in the early stages, poses significant difficulties due to the high similarity and low contrast between cancerous and healthy skin regions. To overcome these challenges, this project implements a various optimization algorithm in conjunction with machine learning and deep learning models. At the core of this approach a Seg-Net architecture is used as task of segmenting skin lesions. This network effectively isolates skin lesions by leveraging both residual connections and recurrent structures, which enhance feature extraction and improve the model's ability to capture contextual information from the images. SegNet-Genetic approach obtained a Jaccard coefficient of 90.48%. In addition to segmentation, skin cancer detection is performed using various Machine and deep learning models, recognized for its capability to retain a rich set of feature representations. In DL, AlexNet model obtained a result as 93.28% accuracy. By merging these state-of-the-art deep learning methodologies with the optimization strength, this project aims to deliver a powerful solution for early skin cancer detection and segmentation, thereby contributing to enhanced diagnostic accuracy and ultimately improving treatment strategies for patients.

திட்ட பணி சுருக்கம்

இந்த திட்டம் மேம்பட்ட ஆழ்ந்த கற்றல் நுட்பங்கள் மற்றும் மேம்படுத்தல் வழிமுறைகளை ஒருங்கிணைப்பதன் மூலம் தோல் புற்றுநோய் கண்டறிதல் மற்றும் துண்டாக்கல் போன்ற மிகப்பெரிய சவாலுக்கு தீர்வை வழங்கும் புதிய அணுகுமுறையாக விளங்குகிறது. தோல் புற்றுநோய் ஒரு முக்கியமான ஆரோக்கியப் பிரச்சனையாக இருக்கும் நிலையில், தகுந்த நேரத்திலான மற்றும் துல்லியமான கண்டறிதல் நோயாளிகளின் விளைவுகளை மேம்படுத்துவதற்கு அவசியமாகின்றது. இருப்பினும், தோல் புற்றுநோயின் தொடக்க நிலைகளில் தோல் புள்ளிகளை துண்டாக்குதல் என்பது புற்றுநோயுள்ள மற்றும் ஆரோக்கியமான தோல் பகுதிகளுக்கு இடையே அதிக ஒற்றுமை மற்றும் குறைந்த எதிர்பார்ப்பு காரணமாக ஒரு முக்கிய சவாலாக உள்ளது. இந்த சவால்களை சமாளிக்க, இந்த திட்டம் பல்வேறு மேம்படுத்தல் வழிமுறைகளுடன் இயந்திர கற்றல் மற்றும் ஆழ்ந்த கற்றல் மாதிரிகளை செயல்படுத்துகிறது. இந்த அணுகுமுறையின் மையத்திலே SegNet கட்டமைப்பு பயன்படுத்தப்படுகிறது, இது தோல் புள்ளிகளை துண்டாக்கும் பணியில் செயல்திறனுடன் செயல்படுகிறது. இந்த நெட்வொர்க் மீதிமுறையைக் (Residual Connections) கொண்டு மற்றும் மறுவரிசை கட்டமைப்புகளை (Recurrent Structures) இணைப்பதன் மூலம் சிறப்பான அம்சங்களை தேடி மற்றும் படங்களில் உள்ள சூழலாற்றலை (Contextual Information) சிறப்பாக பிடிக்க உதவுகிறது. SegNet-Genetic

அணுகுமுறை 90.48% என்ற ஜாக்கார்ட் குணகத்தை (Jaccard Coefficient) பெற்றுள்ளது.

துண்டாக்கலுடன் கூட, தோல் புற்றுநோய் கண்டறிதல் பல்வேறு இயந்திர மற்றும் ஆழ்ந்த கற்றல் மாதிரிகள் மூலம் மேற்கொள்ளப்படுகிறது. ஆழ்ந்த கற்றலில், AlexNet மாதிரி 93.28% துல்லியத்தை (Accuracy) பெற்றுள்ளது. இந்த நிலைநிலையான ஆழ்ந்த கற்றல் முறைகளை மேம்படுத்தல் வலிமையுடன் இணைப்பதன் மூலம், தோல் புற்றுநோயை ஆரம்ப நிலையில் கண்டறிந்து துண்டாக்குவதற்கான ஒரு சக்திவாய்ந்த தீர்வை வழங்குவதே இந்த திட்டத்தின் குறிக்கோள் ஆகும். இது, நோயறிதல் துல்லியத்தை மேம்படுத்துவதோடு, நோயாளிகளுக்கான சிகிச்சைத் திட்டங்களை சிறப்பாக வடிவமைக்க உதவுகிறது.

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LIST OF ABBREVIATIONS

AdaBoost	Adaptive Boosting
ANBO	Artificial Namib Beetle Optimization
Att-UNet	Attention U-Net
CNN	Convolutional Neural Network
Dense Net	Densely Connected Convolutional Network
DSC	Dice Coefficient
IARS	Interpretable Attention Residual Skip connection
IoU	Intersection over Union
LBP	Local Binary Pattern
PSO	Particle Swarm Optimization
Res-Net	Residual Network
R2U-Net	Recurrent Residual U-Net
SAM	Sharpness-Aware Minimization
Seg-Net	Segmentation Network
SVM	Support Vector Machine
TNR	True Negative Rate
TPR	True Positive Rate
VGG	Visual Geometry Group

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

Skin cancer is a prevalent health issue arising from the abnormal growth of skin cells, primarily triggered by excessive exposure to ultraviolet (UV) rays from the sun. This condition affects millions of individuals worldwide, making it one of the most common types of cancer, with melanoma being the most dangerous form. Melanoma develops when pigment-producing cells, known as melanocytes, grow uncontrollably, and if not detected early, it can spread to other parts of the body, leading to severe health complications. The significance of early detection in the fight against skin cancer cannot be overstated, as identifying the disease at its initial stages greatly enhances the chances of successful treatment. However, this can be challenging since cancerous spots often resemble non-cancerous ones, making it difficult for individuals and healthcare providers to distinguish between benign and malignant lesions. To address these challenges, advanced deep learning models have emerged as powerful tools for analyzing skin images. These models automatically identify patterns and features in images, enabling more accurate and quicker detection of skin cancer compared to traditional methods. By training on large datasets that include both cancerous and non-cancerous lesions, deep learning algorithms can effectively differentiate between the two, improving diagnostic accuracy and speed. This application of deep learning in dermatology has the potential to transform patient outcomes by facilitating earlier and more reliable diagnoses, ultimately allowing for timely treatment and significantly enhancing the chances of successful recovery while reducing the overall burden of skin cancer on public health.

1.2 DOMAIN APPLICATION AREAS

Skin cancer detection finds application in various domains, playing a vital role in healthcare, medical imaging, and public health. In healthcare and dermatology, it aids in early diagnosis, treatment planning, and telemedicine, enabling remote consultations and improving access to care, especially in underserved areas. Medical imaging leverages advanced AI and deep learning models to analyze dermoscopic and histopathological images, facilitating accurate and automated diagnostics. Research and development benefit from these tools in advancing drug development, studying cancer progression, and generating data-driven insights to improve outcomes. In education and training, AI-powered systems help train medical professionals and increase public awareness about skin cancer prevention. Consumer technologies, such as skin monitoring apps and wearables, empower individuals to track skin changes and manage UV exposure proactively. Public health initiatives utilize these technologies for mass screening programs and epidemiological studies to address the global burden of skin cancer. Furthermore, insurance and risk assessment integrate predictive analytics to estimate individual risks and refine policy underwriting, while legal and ethical domains apply these technologies in forensic investigations and regulatory policymaking. Collectively, these applications demonstrate the broad impact of skin cancer detection across multiple fields.

1.3 MOTIVATION

The motivation for this research stems from the need to address the critical challenges in timely and accurate diagnosis, which can significantly improve survival rates. Traditional diagnostic methods are time-intensive and heavily reliant on the expertise of dermatologists, leading to subjectivity and variability in assessments. Advanced automated systems for segmentation and classification can provide consistent, accurate, and efficient analysis, reducing the burden on healthcare professionals.

Furthermore, the increasing global incidence of skin cancer highlights the need for scalable solutions capable of handling large datasets with diverse lesion types. Developing such systems can bridge the gap in healthcare access, particularly in underserved regions where specialized medical expertise may not be readily available. The integration of these systems into clinical workflows can not only enhance early detection and treatment but also build patient trust, improve engagement, and ultimately lead to better healthcare outcomes. This research is motivated by the vision of leveraging technology to provide accessible, reliable, and cost-effective tools for combating skin cancer.

1.4 OBJECTIVE

Objectives of the proposed work are as follows

1. To enhance the robustness of the detection algorithm against variations in image quality, lighting conditions, and other real-world factors, ensuring accurate classification of skin lesions in diverse clinical environments.
2. Optimize the model to provide reliable predictions that can assist dermatologists in making early and accurate skin cancer diagnoses.
3. To ensure that models generalize effectively across different datasets and real-world applications.

1.5 PROBLEM STATEMENT

The project aims to develop an AI-based skin cancer detection system utilizing the Kaggle dataset (Skin Cancer: Malignant vs. Benign). This dataset comprises systematically paired dermoscopic and clinical images of various skin lesions, providing a comprehensive resource for training in to deep learning models. The rich clinical metadata included in the dataset, which has a set of skin images along with histopathologic confirmation, enhances the model's ability to accurately classify skin images as benign or malignant. By leveraging this extensive data, the system is designed to assist dermatologists in making early and precise diagnoses of skin cancer. Ultimately, this project seeks to improve diagnostic accuracy, streamline the evaluation process, and support healthcare professionals in delivering timely and effective patient care.

1.6 CHALLENGES

Skin cancer segmentation and classification face significant difficulties due to several factors. Major challenges are as follows

1. The visual similarity between benign and malignant lesions, as both types can exhibit overlapping characteristics, making it hard to distinguish them accurately. Additionally, dermoscopic images often contain artifacts like hair, bubbles, and uneven lighting, which interfere with the clarity of the lesion and complicate both segmentation and classification processes. Furthermore, skin lesions exhibit a wide range of variations in color, size, shape, and texture, which makes it difficult for traditional models to perform well. This diversity in lesion appearance poses a challenge in building models that can generalize effectively across different datasets with such variability.

2. Another significant challenge is the class imbalance in datasets, where malignant lesions are often underrepresented compared to benign ones. This imbalance can lead to biased models that favor the majority class, reducing the sensitivity and accuracy in detecting malignant lesions. Addressing this issue one of the technique such as data augmentation to ensure balanced learning and improved performance across both classes.

3. Early detection is crucial, as skin cancer is most treatable in its initial stages, and such a system can assist in identifying malignant lesions promptly, improving patient outcomes. Additionally, maintaining trust in medical diagnostics is essential, and a reliable system that minimizes diagnostic errors can enhance confidence in AI-assisted tools. This, in turn, fosters greater patient engagement, as individuals are more likely to trust and adhere to recommendations from accurate and effective diagnostic systems. Moreover, by streamlining the diagnostic process, the system can contribute to reducing healthcare costs and supporting continuous monitoring and follow-up, ensuring better long-term care and management of skin cancer cases.

1.7 PROPOSED SOLUTION

This project focuses on developing an advanced AI-based skin cancer detection and segmentation system, addressing the critical challenges associated with early and accurate diagnosis of skin cancer. Using the Kaggle dataset (Skin Cancer: Malignant vs. Benign), which includes systematically paired dermoscopic and clinical images, the project leverages the rich clinical metadata to build a robust model capable of classifying skin lesions as benign or malignant. At the core of the approach is the implementation of a SegNet optimized using the Genetic algorithm. This architecture effectively segments skin lesions by capturing detailed contextual information from images, addressing the challenges of low contrast and high similarity between healthy and cancerous regions. The model has achieved a high level of accuracy, with a Jaccard coefficient of 90.48%, demonstrating its effectiveness in precise lesion segmentation. In addition to segmentation, various machine learning and deep learning models are employed for the classification task, with the genetic algorithm being used for hyperparameter tuning to ensure optimal model performance from the models. By combining these deep learning techniques and optimization algorithms, the project aims to deliver a reliable solution that not only enhances diagnostic accuracy but also generalizes well across different clinical environments and datasets. The classification approach AlexNet achieves 93.28% high accuracy by providing reliable predictions, and improving patient outcomes in the fight against skin cancer.

1.8 ORGANIZATION OF THE PROJECT

The project report is organized as follows: First, an introduction is provided, outlining the objectives and scope of the project, followed by:

1. Chapter 2 discusses the existing systems and various methods required for the proposed system.
2. Chapter 3 discusses the various concepts used in the proposed system, along with the overall system architecture.
3. Chapter 4 discusses the various algorithms and modules implemented.
4. Chapter 5 discusses the results and conclusions derived.
5. Chapter 6 discusses the conclusion and future work.

CHAPTER 2

LITERATURE SURVEY

Recently, research in the field of medical image analysis, particularly skin cancer detection, has seen significant growth. In this section, the recent advancements in skin cancer detection can be summarized. The research can be grouped into key stages: data collection, pre-processing techniques, and model training and detection.

2.1 DATA COLLECTION

Data collection for skin cancer detection primarily involves the use of large, annotated dermoscopic image datasets, including: ISIC (International Skin Imaging Collaboration): This is one of the most widely used datasets for skin lesion analysis. It contains over 25,000 labeled images of various skin conditions, including melanoma and other skin cancers. The ISIC dataset is part of an ongoing international effort to standardize the acquisition, labeling, and analysis of skin images to improve diagnostic accuracy. Researchers often use this dataset to develop models for segmenting skin lesions and classifying them into benign or malignant categories [1]. PH2 Dataset: The PH2 dataset is a smaller, specialized collection of dermoscopic images, specifically designed to differentiate between benign and malignant skin lesions. It includes detailed annotations for each image, making it ideal for research in lesion segmentation and classification. While not as large as the ISIC dataset, PH2 is valuable for focused studies on early-stage skin cancer detection due to its high-quality and well-labeled images [2]. The dataset utilized in this research is a publicly available melanoma dataset, sourced from the University of Córdoba . It is specifically designed for melanoma classification tasks and is categorized into binary and multi-class datasets. The dataset comprises a total of 250 melanoma images, which are grouped based on lesion thickness: 167 melanomas less than 0.76 mm, 54 melanomas between 0.76 mm and 1.5 mm, and 29 melanomas greater than 1.5 mm. From these images, 81 features were extracted, including statistical, morphological, and textural attributes, which are critical for accurate melanoma detection and classification. This dataset provides a robust foundation for experimentation and model validation, facilitating the development of advanced techniques for skin cancer segmentation and classification [3].HAM10000 Dataset: This dataset, known as the "Human Against Machine with 10000 training images," is a large and balanced collection of over 10,000 dermoscopic images, covering a wide range of skin lesion types, including both benign and malignant lesions. HAM10000 is frequently used for training and validating deep learning models because of its diversity and balance, which helps improve the generalization of models across different lesion types. The dataset is instrumental in building robust skin cancer detection systems, as it allows models to learn from a variety of skin conditions [4]. Each of these datasets provides high-quality labeled images, which are crucial for training deep learning models in tasks like segmentation (isolating the lesion) and classification (determining whether the lesion is benign or malignant). Their availability has significantly advanced research in skin cancer detection by providing a standardized set of images for model development and evaluation.

2.2 IMAGE PREPROCESSING TECHNIQUES

Preprocessing techniques play a vital role in preparing dermoscopic images for skin cancer detection by enhancing image quality and ensuring consistency, which improves the performance of deep learning models. These methods help reduce noise, standardize image dimensions, and create variations that allow models to generalize better across different types of skin lesions.

Key preprocessing methods include: Noise Removal: Noise in images, such as random variations in pixel intensity, can interfere with accurate lesion detection. Techniques like Gaussian filtering and Median filtering are used to remove noise and improve the overall clarity of the image [4]. Data augmentation is applied using resizing, rotation, and flipping techniques to enhance the efficiency of the system without requiring new data. The segments, initially of size a × a, are expanded to a maximum size of theta × b, where b is greater than a. This augmentation process helps diversify the dataset while preserving the original information [5]. The resizing operation adjusts the size of an image by arbitrarily selecting the shorter dimension within a specified range, ensuring uniformity in input dimensions. The rotation function rotates the images, specifically by 45°, to increase variability and make the model robust to orientation changes. Additionally, flipping is performed vertically or horizontally based on the object's orientation in the image, further enhancing the dataset's diversity. The final augmented dataset, after applying these transformations, is denoted as E and is crucial for improving the system's performance by exposing it to varied representations of the input data Image Resizing: Deep learning models, especially Convolutional Neural Networks (CNNs), require input images to have uniform dimensions. Resizing images to standard sizes such as 224x224 or 299x299 pixels ensures consistency across the dataset. This not only reduces computational complexity but also allows models to process images efficiently, ensuring that they can learn from all available data regardless of its original size [6]. Contrast Enhancement: Skin lesion images often suffer from low contrast, which makes it difficult to distinguish between healthy skin and cancerous regions. Contrast enhancement techniques, such as contrast stretching, are used to increase the difference in intensity between the lesion and the surrounding skin. This makes the lesion boundaries more distinct, aiding in more accurate segmentation and detection of cancerous areas [3]. Data Augmentation: In medical image analysis, datasets are often limited in size, which can hinder the model's ability to generalize to new, unseen data. Data augmentation techniques artificially expand the dataset by applying transformations like flipping, rotation, zooming, and cropping to the original images. This introduces variability, helping the model become more robust and reducing overfitting. By simulating different real-world conditions, augmentation ensures the model can generalize better and perform well on diverse images during testing [7].

2.3 DEEP LEARNING SEGMENTATION MODELS

Segmentation models play a crucial role in identifying the region of interest (ROI) in dermoscopic images, which is essential for accurately detecting skin lesions. Various models have been developed to address challenges such as low contrast, ambiguous boundaries, and overlapping regions. U-Net is one of the most widely used architectures for medical image segmentation, particularly in tasks like skin lesion segmentation. Its encoder-decoder structure captures both low-level and high-level features by first downsampling to learn compact feature representations and then upsampling to predict the precise location of lesions. Skip connections between corresponding layers in the encoder and decoder help retain fine details during reconstruction, making U-Net effective in detecting small or poorly defined skin lesions [8]. DSGUNet is a U-shaped architecture with a symmetric encoder-decoder structure, designed for efficient feature extraction and segmentation. In the initial three stages, Conditional Parameterized Convolution (CPC) is used for feature extraction, while the later stages utilize Grouped Hadamard Product Attention (GHPA) for multi-perspective feature representation. The Spatial Group Enhanced Attention Mechanism (SGE) is applied across all encoder stages to further refine features. Unlike traditional U-Net, DSGUNet replaces simple skip connections with the Dynamic Group Aggregation Bridge (DAB), which improves feature fusion, reduces noise, and emphasizes relevant semantic regions. Additionally, the model employs multi-scale mask predictions, enhancing training effectiveness and segmentation accuracy [9]. R2U-Net enhances U-Net by integrating residual connections and recurrent layers to improve segmentation accuracy. Residual connections allow the model to bypass unnecessary layers, reducing vanishing gradient issues and enabling deeper networks, while recurrent layers help capture long-range dependencies within the data. This combination makes R2U-Net particularly effective in identifying subtle or irregular skin lesions [10]. Fuzzy U-Net, on the other hand, incorporates fuzzy logic into the segmentation process. This is beneficial for handling uncertain or ambiguous lesion boundaries, which are common in medical images where lesions may overlap with healthy tissue. By using fuzzy sets, Fuzzy U-Net can manage data uncertainties, improving segmentation in cases where traditional models struggle with unclear lesion boundaries [7]. IARS SegNet is an improved version of SegNet, incorporating attention mechanisms and skip connections to enhance both accuracy and interpretability. The attention mechanisms allow the model to focus on the most relevant parts of the image, enhancing its ability to detect lesions even in complex backgrounds. Skip connections, as seen in U-Net, ensure that spatial information is preserved throughout the network, leading to accurate and detailed segmentation results. This model is particularly effective in medical imaging where precision is critical [11].

2.4 FEATURE EXTRACTION TECHNIQUES

Feature extraction is a critical step in skin lesion classification as it helps isolate essential characteristics from images, such as color, texture, and shape. Convolutional Neural Networks (CNNs) are widely used for this purpose due to their ability to automatically extract hierarchical features from input images. CNNs capture essential elements like edges, textures, and shapes, making them highly effective for identifying different types of skin lesions by progressively learning more complex patterns [3]. ResNet-50, a deeper architecture, enhances this process by introducing residual connections.

These connections help prevent the vanishing gradient problem that typically occurs in very deep networks, ensuring that ResNet-50 can effectively extract features even from complex datasets [12]. Similarly, VGG-19 is another popular architecture known for its depth and simplicity. It uses small convolutional filters to extract fine-grained details from images, which is particularly useful for tasks requiring detailed feature extraction, such as skin lesion classification [6]. These models play a vital role in ensuring that critical features of skin lesions are accurately captured for subsequent classification. Advanced feature extraction techniques to enhance the analysis of skin cancer images. The Contourlet Transform (CT) is employed to analyze the borders, contrast changes, and shapes of the lesions by decomposing images into sub-bands using a filter bank. It further incorporates directional filter banks, providing a multi-scale and multi-directional representation that accurately captures contours and fine details. Additionally, the Local Binary Pattern (LBP) is used as a texture descriptor by comparing the gray levels of neighboring pixels to assign binary values, generating a histogram-based feature vector. These combined techniques ensure a comprehensive extraction of features crucial for accurate classification and analysis of skin cancer images [13].

2.5 SKIN CANCER CLASSIFICATION

Classification models are essential for predicting whether a skin lesion is benign or malignant after the processes of segmentation and feature extraction have been completed. ResNet-50 demonstrates superior performance in skin cancer detection, achieving an average testing accuracy of 82.87%. Furthermore, the model's loss significantly decreases from 0.7 to 0.4. It is suggested that with further hyperparameter tuning, the model's accuracy could be enhanced, and the loss reduced even further [14]. Convolutional Neural Networks (CNNs) are among the most widely used models for skin cancer classification, effectively distinguishing between malignant melanoma and benign lesions by analyzing patterns and textures within the images [3]. ResNet-50 is another prevalent deep learning model known for its performance in image classification tasks. Its architecture incorporates residual connections, which facilitate the training of deeper networks and make it particularly suitable for diagnosing skin cancer [12]. Inception-ResNet-v2 further enhances classification performance by combining the strengths of Inception and ResNet architectures. This model achieves high classification accuracy while maintaining relatively low computational costs, making it efficient for skin cancer classification tasks. It has been fine-tuned for both binary and multi-class classification scenarios, demonstrating strong performance in differentiating between various types of skin lesions [15]. Additionally, ensemble methods play a crucial role in improving classification accuracy by combining multiple classifiers, such as Support Vector Machines (SVM), Logistic Regression, and VGG-19. By leveraging the strengths of various algorithms, ensemble models enhance prediction reliability and robustness, leading to improved diagnostic outcomes in skin cancer classification [6].

2.6 SUMMARY

In recent years, deep learning techniques have gained significant traction in the field of medical image analysis, particularly in the identification and diagnosis of skin cancer. These advancements rely on the use of large, publicly available datasets such as ISIC, PH2, and HAM10000, which provide thousands of labeled dermoscopic images that are essential for training models to distinguish between benign and malignant skin lesions. Effective data preprocessing techniques, including noise removal, image resizing, contrast enhancement, and data augmentation, are employed to improve the quality and consistency of these images, ensuring that the models can generalize well and achieve high accuracy. Segmentation models like U-Net, R2U-Net, Fuzzy U-Net, and IARS SegNet have proven instrumental in isolating the region of interest typically the skin lesion from the surrounding skin in dermoscopic images. These models use deep neural network architectures to perform precise lesion segmentation, which is a critical step in the diagnostic process. Convolutional Neural Networks (CNNs) and more advanced architectures like ResNet-50 and VGG-19 are commonly used for feature extraction, capturing important characteristics such as texture, color, and shape, which are essential for accurate classification. Following segmentation and feature extraction, classification models determine whether the identified lesion is benign or malignant. Models like CNNs, ResNet-50, and Inception-ResNet-v2 have demonstrated high accuracy in these tasks, with some studies also exploring ensemble methods that combine multiple classifiers to enhance performance further. Despite these advances, challenges remain, including the need for more diverse, annotated datasets and improving the generalization of models across different skin types and conditions. Nonetheless, these deep learning techniques offer promising tools for early detection and diagnosis of skin cancer, supporting clinicians in making more accurate and timely decisions, which can lead to better patient outcomes.

CHAPTER 3

SYSTEM DESIGN

3.1 SYSTEM ARCHITECTURE

This system design outlines an AI pipeline for skin lesion analysis which is given in Figure 3.1. It starts with dataset preprocessing, followed by segmentation models (like Pyramid U-Net, R2U-Net, and Seg-Net) to extract relevant lesion areas, with Seg-Net selected as the best model. Data

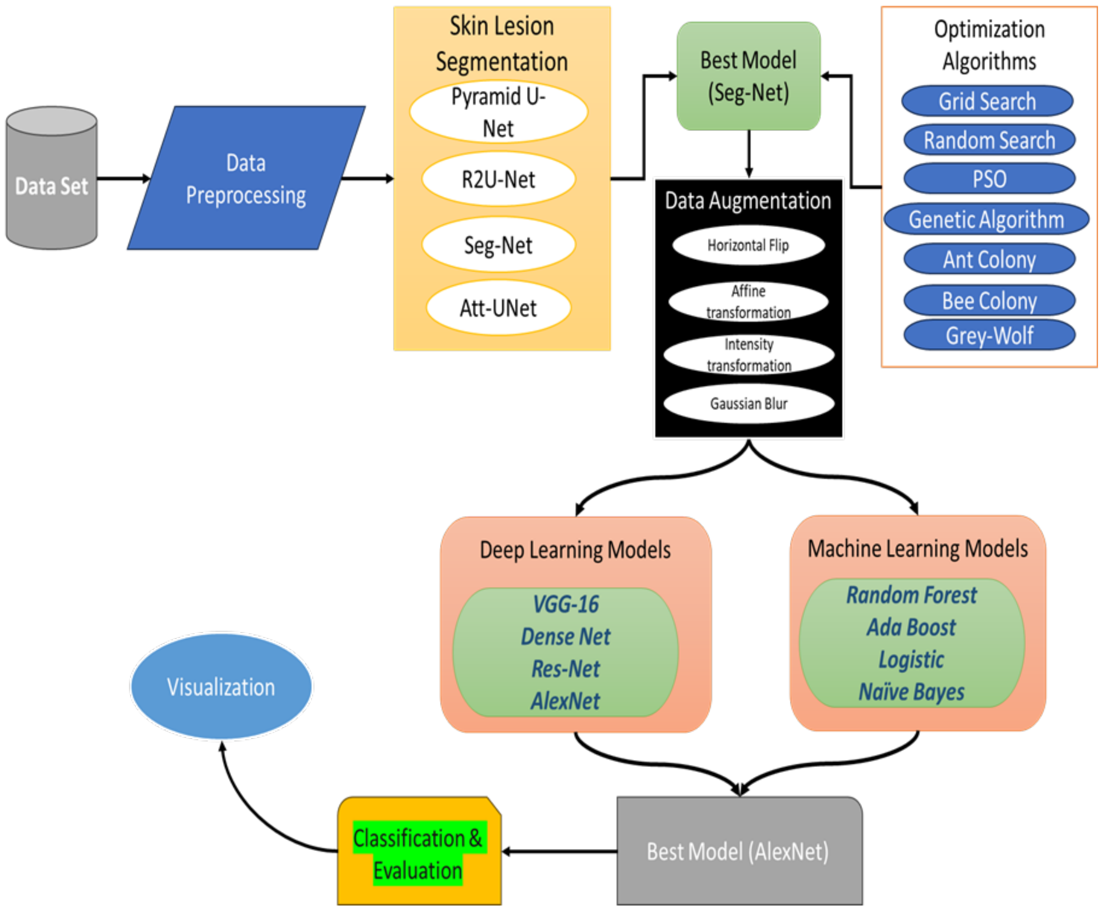

Figure 3.1: Architecture diagram of the Proposed System

augmentation techniques (e.g., horizontal flip, affine, Gaussian and intensity transformations) enhance the training set. Deep learning models (e.g., VGG-16, DenseNet, ResNet) and machine learning classifiers (e.g., Random Forest, AdaBoost, Naïve Bayes) perform lesion classification. Optimization algorithms, such as PSO and Genetic Algorithm, fine-tune the models, leading to a final evaluation and visualization stage for results.

3.2 DATA COLLECTION AND PREPROCESSING

Data collection involves obtaining a labeled dataset of skin lesion images from a reliable source, such as this Kaggle dataset [16], which contains 3,297 images. This dataset includes two primary classes: malignant (cancerous) and benign (non-cancerous). In Data Pre-Processing Standardizing all images to a fixed size 128x128 ensures consistency in input dimensions, which is crucial for batch processing in deep learning models. Scaling pixel values to a range of 0 to 1 helps improve model convergence by ensuring uniform input intensity. Dividing the dataset into training, validation, and test sets to evaluate model performance and generalization ability accurately.

3.3 SKIN LESIONS SEGMENTATION MODELS

Segmentation identifies the boundaries of the skin lesion, separating it from other skin areas. This boundary information can improve feature extraction, as the model can analyze only the lesion instead of irrelevant skin textures. Advanced deep learning models are typically used for this task. Common models include

- Pyramid U-Net: An architecture that enhances U-Net by incorporating pyramid pooling for capturing context at multiple scales.

- R2U-Net: A model combining U-Net with residual and recurrent connections to improve segmentation performance.
- Seg-Net: A deep learning architecture designed for semantic segmentation.
- Att-UNet: An attention-based U-Net that uses attention mechanisms to focus on important features in the image.

The Best Model for segmentation is selected based on performance metrics, and here, Seg-Net is the best model.

3.3.1 SEG-NET

SegNet uses an encoder-decoder structure. The encoder extracts feature from the input image using convolutional and pooling layers, while the decoder reconstructs the segmented output from the encoded features. The encoder in SegNet is often based on the convolutional layers of VGG-16. A key feature of SegNet is its efficient upsampling technique. Instead of learning to upsample from scratch, SegNet uses the pooling indices from the encoder layers during the decoder phase. This approach allows for more accurate and efficient reconstruction of the segmented output. SegNet does not use any fully connected layers. This makes it suitable for processing images of varying sizes and reduces the overall number of parameters, further enhancing computational efficiency. The architecture of SegNet is given in Figure 3.2.

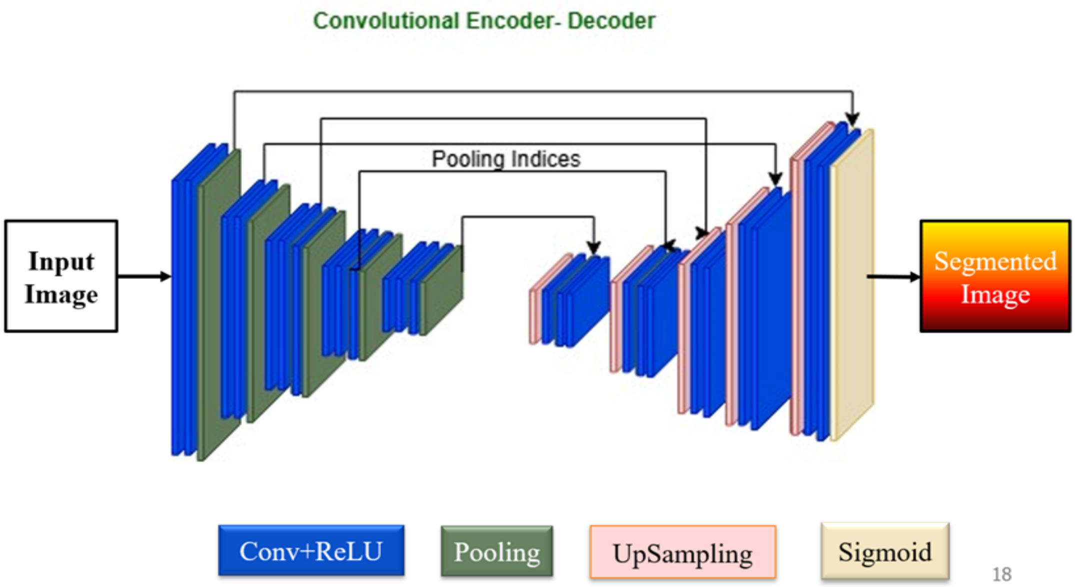

Figure 3.2: Architecture of Seg-Net

3.4 OPTIMIZATION ALGORITHMS

Optimization algorithms are techniques designed to find the best solution to a problem from a set of possible solutions. They're widely used in various fields like engineering, finance, machine learning, and artificial intelligence to improve performance, minimize costs, or maximize efficiency. They begin with an initial guess or population of solutions. Then, they iteratively improve these solutions based on criteria (e.g., minimizing an error function in machine learning). The algorithm stops when it finds a satisfactory solution or reaches a maximum number of iterations. Different types of optimization algorithms are used such as Grid Search, Random Search, PSO, Genetic Algorithm, Ant colony, Bee colony and Grey wolf optimization Algorithm which are discussed below.

- Grid Search: An exhaustive search over specified parameter values.
- Random Search: A random sampling of parameter values.

- PSO (Particle Swarm Optimization): An optimization technique inspired by the social behavior of birds and fish.
- Genetic Algorithm: An evolutionary algorithm based on the principles of natural selection.
- Ant Colony: An optimization method inspired by the foraging behavior of ants.
- Bee Colony: A technique inspired by the natural behavior of honey bees in finding food sources.
- Grey-Wolf: An algorithm inspired by the social hierarchy and hunting mechanism of grey wolves.

3.5 AUGMENTATION METHODS

Data augmentation is a technique used to artificially increase the size and diversity of a training dataset by applying various transformations to existing data. In the context of skin cancer detection, data augmentation helps improve model generalization by creating variations in the dataset, making the model more robust to differences in real-world images. This is especially useful when working with limited medical image datasets, as it helps prevent overfitting and improves model performance. Three types of augmented methods are used first one is Horizontal Flip: The image is flipped horizontally (left to right), creating a mirrored version of the image. This technique helps make the model more robust to symmetrical variations in the data. Rotation: The image is rotated by 15 degrees around its center point. Second one is Rotation which helps the model become invariant to orientation changes, making it better at recognizing features regardless of slight rotations. Final one is Intensity Scaling: The brightness of the image is increased by scaling pixel values with alpha=1.1 (which slightly enhances contrast) and beta=30 (which increases brightness).

3.6 MACHINE LEARNING CLASSIFICATION MODELS

Machine learning classification models are algorithms designed to categorize data into specific classes based on learned patterns. In skin cancer detection, for example, these models might classify images as either benign (non-cancerous) or malignant (cancerous). The process begins with training, where the model learns from labelled examples to recognize key features that distinguish each class. Feature extraction is done by VGG-16 and the classification models include Random Forest, AdaBoost, Logistic Regression, and Support Vector Machines (SVM) uses the extracted features and classify the results. Various ML models used in this project are discussed below.

- Random Forest is an ensemble method that builds multiple decision trees, each trained on different data samples. It then combines their outputs for improved accuracy and robustness, reducing the risk of overfitting on complex datasets.
- AdaBoost (Adaptive Boosting) is another ensemble method that combines weak learners, typically decision trees, to create a stronger classifier. It adjusts the weights of misclassified examples, focusing more on difficult cases in each iteration.
- Logistic Regression is a simple, interpretable model for binary classification. It calculates probabilities based on a logistic function, making it a good baseline method, although it may not capture complex patterns as well as other models.
- Naive Bayes is a family of simple probabilistic classifiers based on applying Bayes' Theorem with strong independence assumptions.

Each of these models has strengths and limitations. Ensemble methods like Random Forest and AdaBoost are often favored for their accuracy and resilience to overfitting. These models are often fine-tuned through hyperparameter optimization to maximize classification performance, making them essential tools in various classification tasks, including medical image analysis for early disease diagnosis.

3.7 DEEP LEARNING CLASSIFICATION MODELS

Deep learning classification models are powerful algorithms in image-based tasks like skin cancer detection, where they automatically learn to recognize complex patterns within images. These models, including VGG-16, DenseNet, ResNet, and AlexNet use multiple layers to extract hierarchical features, making them particularly well-suited for tasks requiring detailed feature detection and differentiation. Various DL models used in this project are discussed below.

- VGG-16 is a deep CNN with 16 layers that uses small filters to capture intricate details in images. This model is known for its simplicity and effectiveness, making it widely used in image classification tasks. However, it requires significant computational resources due to its depth and number of parameters.
- DenseNet (Densely Connected Convolutional Network) connects each layer to every other layer in a ”dense” manner, allowing for efficient information flow and reuse of features, which improves model performance and reduces the risk of overfitting. DenseNet is computationally efficient and is especially useful when data is limited, as it maximizes feature usage.
- ResNet (Residual Network) introduces skip connections, allowing

gradients to flow more easily through the network, which prevents the model from degrading in performance as it deepens. This approach enables very deep networks (e.g., ResNet-50 or ResNet-101) to maintain accuracy, making ResNet ideal for complex image classification tasks like medical diagnosis.

- AlexNet is one of the pioneering architectures in Convolutional Neural Networks (CNNs) that revolutionized deep learning for image recognition. It consists of multiple convolutional and pooling layers, followed by fully connected layers, designed to efficiently capture spatial hierarchies in images. AlexNet introduced key innovations like ReLU activations, dropout for regularization, and GPU-based training, enabling it to learn complex features like edges, textures, and shapes. This architecture laid the foundation for distinguishing between classes such as benign and malignant skin lesions in medical imaging tasks.

3.7.1 ALEXNET

AlexNet, introduced in 2012 by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, is a deep Convolutional Neural Network (CNN) architecture that revolutionized the field of computer vision. It gained widespread attention for winning the ImageNet Large Scale Visual Recognition Challenge, drastically reducing the error rate and outperforming traditional methods. In Figure 3.3 AlexNet architecture consists of 8 layers, including 5 convolutional layers followed by 3 fully connected layers. AlexNet utilized the ReLU activation function, which sped up training by mitigating the vanishing gradient problem, and employed GPU acceleration to handle the large dataset. Additionally, it introduced regularization techniques like dropout to prevent overfitting. This model laid the foundation for more complex architectures, such as VGG,

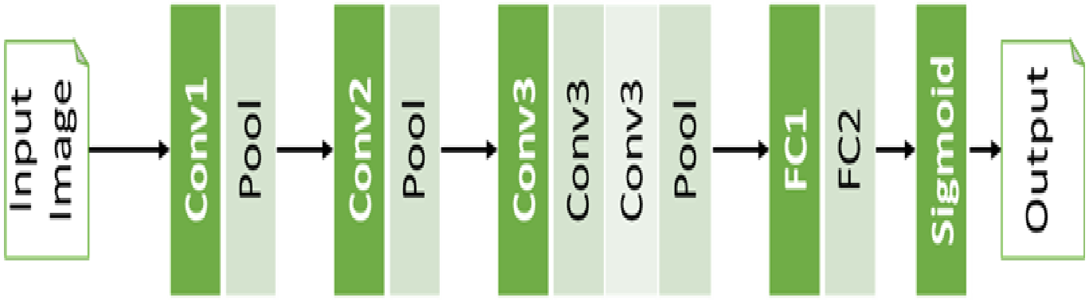

Figure 3.3: Architecture of AlexNet

ResNet, and others, driving the widespread adoption of deep learning in image classification tasks.

3.8 SUMMARY

The proposed methodology begins with data preprocessing, where images are resized to 128x128 pixels, scaled for consistency, and divided into training and testing sets. The system incorporates advanced segmentation models such as Pyramid U-Net, R2U-Net, and SegNet, with SegNet identified as the best-performing model due to its efficient encoder-decoder structure and computational simplicity. SegNet utilizes techniques like pooling indices for upsampling, enhancing its ability to segment lesions with high precision. The chapter also discusses data augmentation methods like horizontal flips, rotations, and intensity scaling, which improve model robustness by increasing dataset diversity. Optimization algorithms, including Particle Swarm Optimization (PSO), Grid search, Random search, Ant colony, Bee colony and Genetic Algorithms, are employed to fine-tune model parameters. Additionally, machine learning classifiers like Random Forest, Naive Bayes, Logistic Regression, and AdaBoost, alongside deep learning models such as VGG-16, DenseNet, ResNet and AlexNet, are used for lesion classification, providing a comprehensive approach to detecting and categorizing skin lesions.

CHAPTER 4

ALGORITHM AND IMPLEMENTATION

This section includes the definition of the logics and steps to solve the above-mentioned problem statement. The proper description of the used algorithms can be ordered with the steps.

4.1 IMAGE SEGMENTATION USING SEG-NET

SegNet segments an image using an encoder-decoder structure. The encoder reduces the image size through convolutional and max-pooling layers, capturing essential features while discarding unnecessary details. The decoder then upsamples these features using the saved pooling indices, effectively restoring spatial resolution and creating a segmented mask. The working procedure is given in Algorithm 4.1.

4.2 GENETIC ALGORITHM

Hyperparameter optimization is a critical task in machine learning and deep learning, as selecting the right set of hyperparameters can significantly impact model performance. Traditional methods of hyperparameter tuning, such as grid search or random search, can be computationally expensive and may not efficiently explore the entire search space. A genetic algorithm (GA) offers a biologically inspired optimization approach that mimics the process of natural selection to find the optimal set of hyperparameters. In the context of hyperparameter optimization, the genetic algorithm works by evolving a population of candidate solutions (individuals) over multiple generations. Each individual represents a set of hyperparameters, and the algorithm uses selection, crossover, and mutation to generate new individuals that are more likely to perform well. The fitness of each individual is evaluated based on model performance, and the best individuals are kept to form the next generation. This process continues until an optimal or satisfactory solution is found. By applying genetic algorithms, there by automating the process of hyperparameter tuning, potentially finding better solutions. The working procedure for genetic algorithm is given in Algorithm 4.2.

4.3 DATA AUGMENTATION

Image augmentation is a technique used in machine learning and computer vision to artificially expand the size and diversity of a dataset by applying various transformations to the existing images. This process is essential for improving model generalization, preventing overfitting, and enhancing the performance of deep learning models. The working procedure of data augmentation is given in Algorithm 4.3.

4.4 ALEXNET

The architecture consists of 8 layers, including 5 convolutional layers followed by 3 fully connected layers. AlexNet utilized the ReLU activation function, which sped up training by mitigating the vanishing gradient problem, and employed GPU acceleration to handle the large dataset. Additionally, it introduced regularization techniques like dropout to prevent overfitting. This model laid the foundation for more complex architectures, such as VGG, ResNet, and others, driving the widespread adoption of deep learning in image classification tasks. The working procedure of AlexNet is given in Algorithm 4.4.

Algorithm 4.1 Image Segmentation using SegNet

1: **Input:** Pre-processed image of a skin lesion.

2: **Initialize:** SegNet Model:

- Set up the encoder-decoder architecture of SegNet.
- Load pre-trained weights if using transfer learning for initialization.

3: **Encoding Stage:**

- Pass the input image through a series of convolutional
- For each convolutional layer:Apply convolution filters to extract feature maps.

$$F(x,y) = \sum_{i=-k}^{k} \sum_{j=-k}^{k} W(i,j) \cdot I(x+i, y+j) + b$$

where $F(x,y)$ is the output, $W(i,j)$ are weights, $I(x,y)$ is the input, and b is the bias term.

- Apply ReLU activation to introduce non-linearity.

$$\text{ReLU}(x) = \max(0,x)$$

- For each pooling layer:Downsample the feature maps using max pooling to reduce dimensionality.
- Store the max pooling indices for later use in the decoding stage.

4: **Decoding Stage:**

- Pass the encoded feature maps through a series of upsampling and convolutional layers in the decoder.
- For each upsampling layer:
- Use the stored max pooling indices to upsample feature maps to the original resolution.
- For each convolutional layer in the decoder: Apply convolution filters to refine feature maps and restore spatial resolution.
- Apply ReLU activation to enhance non-linearity in the output.

5: **Segmentation Output:**

- Pass the final feature map through a sigmoid for binary segmentation.

$$\sigma(x) = \frac{1}{1+e^{-x}},$$

- Generate a segmented mask with each pixel assigned a class label

6: **Output:** Segmented mask of the skin lesion.

Algorithm 4.2 Genetic Algorithm

1: **Parameter Space:** Define the hyperparameters (e.g., learning rate, filters) and their possible ranges:

$$\text{Parameter Space} = \{P_1, P_2, \ldots, P_n\}, \quad P_i \in [a_i, b_i]$$

2: **Random Individual:** Generate a random individual I by selecting values for hyperparameters:

$$I = (P_1^*, P_2^*, \ldots, P_n^*) \quad \text{where } P_i^* \in [a_i, b_i]$$

3: **Fitness:** Evaluate the fitness $f(I)$ of an individual based on validation accuracy:

$$f(I) = \frac{\text{Correct Predictions}}{\text{Total Predictions}}$$

4: **Selection:** Select N_s individuals with the highest fitness scores:

$$\text{Selected Population} = \{I_1, I_2, \ldots, I_{N_s}\} \quad \text{where } f(I_k) \geq f(I_j), \forall k, j$$

5: **Crossover:** Combine two parent individuals I_1, I_2 to create a child individual I_c:

$$P_i^c = \begin{cases} P_i^1, & \text{if } r < 0.5 \\ P_i^2, & \text{otherwise} \end{cases}$$

where r is a random number $r \sim U(0,1)$.

6: **Mutation:** Mutate an individual I by randomly altering a hyperparameter P_i:

$$P_i' = P_i + \varepsilon, \quad \varepsilon \sim N(0, \sigma^2)$$

where ε is Gaussian noise with mean 0 and variance σ^2.

7: **GA Loop:** Repeat steps 4–6 for G generations, iteratively improving the population:

$$\text{New Population} = \text{Selection} + \text{Crossover} + \text{Mutation}$$

8: **Final Result:** Return the best-performing individual:

$$I^* = \arg\max_I f(I)$$

Algorithm 4.3 Data Augmentation

1: Horizontal Flip:

- Input: Original image.
- Process: Flip the image horizontally (left to right).
- Output: A mirrored version of the original image.
- Purpose: Make the model more robust to symmetrical variations in the data.

2: Rotation:

- Input: Original image.
- Process: Rotate the image by 15 degrees around its center point.
- Output: A rotated version of the original image.
- Purpose: Make the model invariant to orientation changes, improving its ability to recognize features despite slight rotations.

3: Intensity Scaling:

- Input: Original image (with pixel values).
- Process: Multiply pixel values by alpha = 1.1 to enhances contrast and add beta = 30 to the pixel values to increases brightness.
- Output: A version of the original image with enhanced brightness and contrast.
- Purpose: Improve the model's robustness to variations in lighting conditions and contrast

4: Gaussian Blur:

- Input: Original image (with pixel values).
- Process: Convolve the image with a Gaussian filter defined by kernel size K×K also each pixel is replaced by the weighted average of its neighbors based on the Gaussian distribution.
- Output: A smoothed version of the original image with reduced noise
- Purpose: Enhance the model's ability to generalize by simulating slight blurring or out-of-focus conditions, often encountered in real-world scenarios

Algorithm 4.4 Image classification using AlexNet

1: **Input Layer:** The network takes input images of size $128 \times 128 \times 3$ (height $\times$ width $\times$ channels). Images are typically resized and normalized before being fed into the network.

2: **Convolutional Layers (Feature Extraction):**

- **Layer 1:** Applies 96 filters of size 11×11, with stride 4×4, followed by ReLU activation. Outputs feature maps of size $30 \times 30 \times 96$.
- Max pooling with a pool size of 3×3 and stride 2×2, followed by Batch Normalization.
- **Layer 2:** Applies 256 filters of size 5×5, with stride 1×1, padding set to ”same,” followed by ReLU activation. Outputs feature maps of size $15 \times 15 \times 256$.
- Max pooling with a pool size of 3×3 and stride 2×2, followed by Batch Normalization.
- **Layer 3:** Applies 384 filters of size 3×3, padding set to ”same,” followed by ReLU activation. Outputs feature maps of size $15 \times 15 \times 384$.
- **Layer 4:** Applies another 384 filters of size 3×3, padding set to ”same,” followed by ReLU activation. Outputs feature maps of size $15 \times 15 \times 384$.
- **Layer 5:** Applies 256 filters of size 3×3, padding set to ”same,” followed by ReLU activation. Outputs feature maps of size $15 \times 15 \times 256$.
- Max pooling with a pool size of 3×3 and stride 2×2. The spatial dimensions reduce to $7 \times 7 \times 256$.

3: **Fully Connected Layers (Classification):**

- **Layer 6:** A fully connected layer with 4096 neurons and ReLU activation. Dropout with a rate of 0.5 is applied to prevent overfitting.
- **Layer 7:** Another fully connected layer with 4096 neurons and ReLU activation. Dropout with a rate of 0.5 is applied to prevent overfitting.

4: **Output Layer:** A fully connected layer with 1 neuron and a sigmoid activation function to output class probabilities for binary classification.

5: **Regularization:**

- **Batch Normalization:** Applied after certain layers to normalize activations and improve stability.
- **Dropout:** Applied with a rate of 0.5 in fully connected layers to prevent overfitting by randomly deactivating some neurons during training.

4.5 SUMMARY

The Algorithm and Implementation details the logic behind the project's core modules. SegNet is utilized for image segmentation, employing an encoder-decoder architecture that processes input images into segmented masks by leveraging convolutional layers, pooling indices, and upsampling techniques. A Genetic Algorithm is applied for hyperparameter optimization, mimicking natural selection through selection, crossover, and mutation processes to enhance model performance. Data augmentation techniques, including transformations like rotation and intensity scaling, are implemented to artificially expand the dataset and improve model generalization. For classification, AlexNet is described as the primary deep learning architecture, consisting of convolutional and fully connected layers with innovations like ReLU activations and dropout to prevent overfitting.

CHAPTER 5

RESULTS AND DISCUSSIONS

This chapter consists of results of all the above modules and evaluation metrics of the model implemented.

5.1 EVALUATION METRICS

Evaluation metrics are quantitative measures used to assess the performance of a machine learning model. They provide insights into how well a model predicts or classifies data compared to ground truth labels. These metrics help determine a model's effectiveness, guiding improvements and comparing different models or techniques.

5.1.1 EVALUATION METRICS FOR SEGMENTATION

1. Jaccard Coefficient (IoU): The degree of variety and similarity between sample sets is gauged by the IoU is given in Equation (5.1). The size of the intersection can be calculated by dividing it by the size of the union of the sample sets, where A is the predicted mask and B is the true mask.

$$(A,B) = \frac{|A \cap B|}{|A \cup B|} \tag{5.1}$$

2. The Dice coefficient: The Dice Coefficient, or Dice Similarity Coefficient (DSC), is very similar to the Jaccard Coefficient and is particularly used to gauge the similarity between two sets. It's

especially common in binary image segmentation given in Equation (5.2).

$$\text{Dice} = \frac{2 \times |A \cap B|}{|A| + |B|} \tag{5.2}$$

5.1.2 EVALUATION METRICS FOR CLASSIFICATION

1. Accuracy: Measures the overall correctness of the model. The correctness of the model is calculated using the Equation (5.3).

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FN} + \text{FP}} \tag{5.3}$$

2. Precision for Malignant (Positive Predictive Value): Measures the proportion of true malignant predictions. Positive Predicted Value is calculated by using the Equation (5.4).

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{5.4}$$

3. Recall for Malignant (Sensitivity or True Positive Rate): Measures how many malignant cases were correctly identified. True Positive Rate is calculated by using the Equation (5.5).

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{5.5}$$

4. F1 Score: Harmonic mean of precision and recall. F1 Score is calculated by using the Equation (5.6).

$$\text{F1 Score} = \frac{2 \cdot (\text{Precision} \cdot \text{Recall})}{\text{Precision} + \text{Recall}} \tag{5.6}$$

5. Specificity: The specificity of a classifier, also known as the True Negative Rate (TNR), measures the proportion of actual benign

cases that are correctly identified as benign. True Negative Rate is calculated by using the Equation (5.7).

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{5.7}$$

5.2 DATA AUGMENTATION RESULTS

Original images for benign is 1800 and malignant is 1497. After segmentation various data-augmented techniques were used like gaussian blur, affine transformation, horizontal flip, and color transformation, to increase the data size and the augmented images from the segmented image sample is given in Figure 5.1. Augmented details for classification is given in Table 5.1. A total of 19692 images are used for classification, where 15825 images are used for training and 3957 images are used for testing.

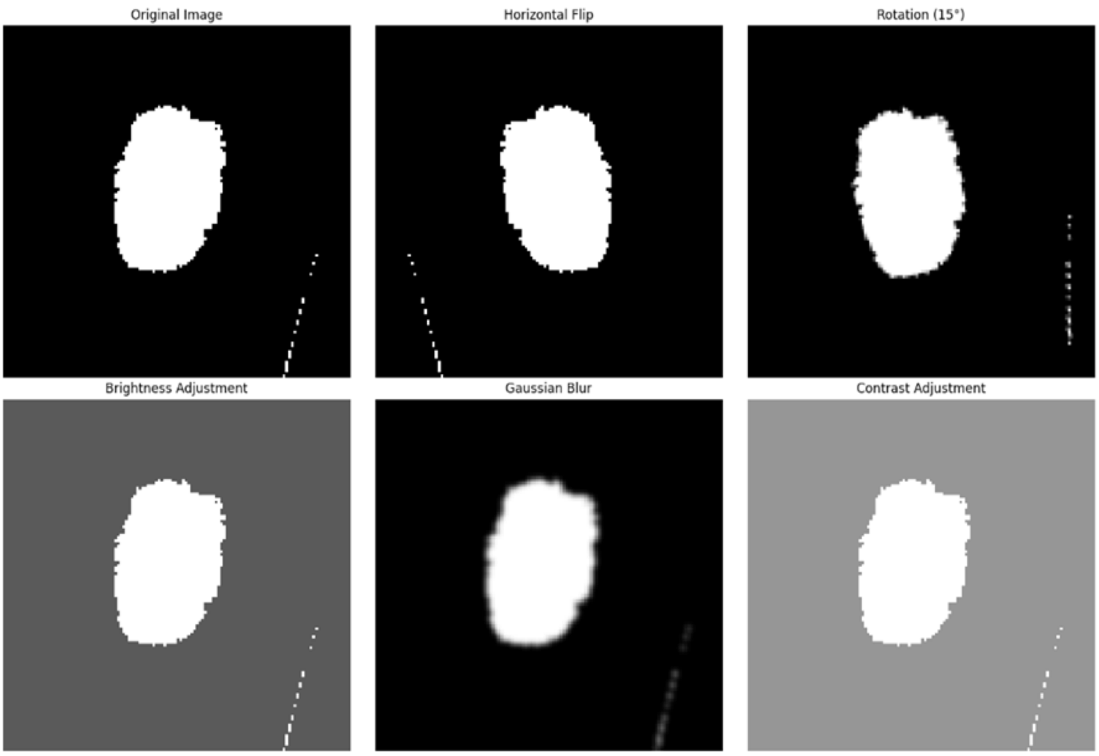

Figure 5.1: Augmented images from Segmented image

Table 5.1: Count for Original and Augmented images

Original Images	Augmented Images	Total Images
Benign: 1800	Benign:9000	10800
Malignant: 1497	Malignant: 7485	8892
		19692

5.3 SEGMENTATION RESULTS

The image illustrates the process of segmenting a skin lesion for analysis. The original input image, showing the lesion with its natural features such as color, texture, and shape. An intermediate stage in the segmentation process, where an initial mask is generated to roughly identify the lesion. This step likely involves techniques such as thresholding or region-growing. The predicted segmentation mask, where the lesion is accurately isolated from the background and the results is given in Figure 5.2. This predicted mask is critical for tasks like lesion classification or further medical analysis.

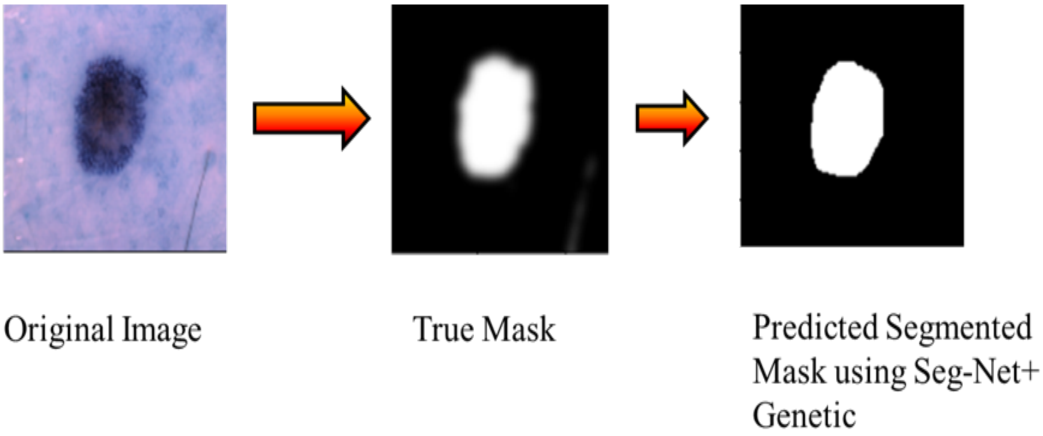

Figure 5.2: Actual mask and Predicted mask

R2U-Net, Pyramid-UNet, SegNet, Att-Unet individual models results are shown in Table 5.2. Where Segnet achieved good IOU compared to other segmentation models and segNet is applied with various optimizers and the result are shown in Table 5.3. SegNet generally performs the best across the models in the first table. Among optimization techniques, Genetic Algorithm significantly boosts SegNet's performance, achieving the highest Jaccard and Dice scores. Among these techniques, Genetic Algorithm optimization provides the best improvement, with a Jaccard score of 90.48% and a Dice score of 95.00%. This demonstrates that optimization algorithms can significantly enhance the model's segmentation accuracy.

Table 5.2: Model Performance Comparison

Model	Jaccard	Dice
R2U-Net	81.37%	89.79%
Pyramid-Unet	83.91%	91.25%
SegNet	**87.52%**	**93.34%**
Att-Unet	75.94%	86.32%

Table 5.3: Model Performance Comparison

Model	Optimizer	Jaccard	Dice
SegNet	Grid Search	89.97%	94.72%
SegNet	Random Search	88.57%	93.94%
SegNet	**Genetic Algorithm**	**90.48%**	**95.00%**
SegNet	PSO (Particle Swarm Optimization)	89.22%	94.30%
SegNet	Ant Colony	88.32%	93.79%
SegNet	Bee Colony	90.37%	94.94%
SegNet	Grey Wolf	87.22%	93.17%
R2U-Net	ANBO	87.20%	93.16%
SegNet	ANBO	88.64%	93.98%

5.4 RESULT ANALYSIS OF CLASSIFICATION ALGORITHM USING MACHINE LEARNING

The Table 5.4 compares the accuracy of four machine learning models: Random Forest, AdaBoost, Logistic Regression, and Naïve Bayes. The Random Forest model achieves the highest accuracy, indicating it is the most accurate in classifying the data.

Table 5.4: Machine Learning Comparison

Model	Accuracy	Precision	Recall	Specificity	F1-Score
Random Forest	**89.31%**	**88.60%**	**87.45%**	**90.83%**	**88.02%**
Ada Boost	80.01%	79.42%	74.90%	84.17%	77.09%
Logistic Regression	86.58%	86.18%	83.51%	89.08%	84.82%
Naïve Bayes	73.81%	80.75%	54.76%	89.36%	65.26%

5.5 RESULT ANALYSIS OF CLASSIFICATION ALGORITHM USING DEEP LEARNING

The Table 5.5 compares the performance of four deep learning models—VGG-16, ResNet, AlexNet, and DenseNet—across key evaluation metrics: Accuracy, Precision, Recall, Specificity, and F1-Score. Among the models, AlexNet stands out with the highest accuracy (93.28%) and F1-Score (92.51%), demonstrating a balanced performance across all metrics. VGG-16 closely follows, achieving 93.05% accuracy, the highest precision (94.02%), and specificity (95.32%), making it excellent at minimizing false positives. ResNet, on the other hand, performs the worst, with an accuracy of 82.89% and noticeably lower precision, recall, and F1-Score, suggesting it may not be well-suited for this dataset. DenseNet shows reasonable performance with 91.08% accuracy and good recall (87.23%), but it falls short of AlexNet and VGG-16. AlexNet's strong recall (92.46%) makes it particularly effective at identifying true positives, while VGG-16 excels in precision and specificity. Overall, AlexNet is the most robust model for this task, though the final choice should also account for factors like computational efficiency and the confusion matrix for the AlexNet is given in Figure 5.3.

Table 5.5: Deep Learning Comparison

Model	Accuracy	Precision	Recall	Specificity	F1-Score
VGG-16	93.05%	94.02%	90.26%	95.32%	92.10%
ResNet	82.89%	85.48%	74.56%	89.68%	79.65%
AlexNet	**93.28%**	**92.56%**	**92.46%**	**93.94%**	**92.51%**
DenseNet	91.08%	92.48%	87.23%	94.22%	89.78%

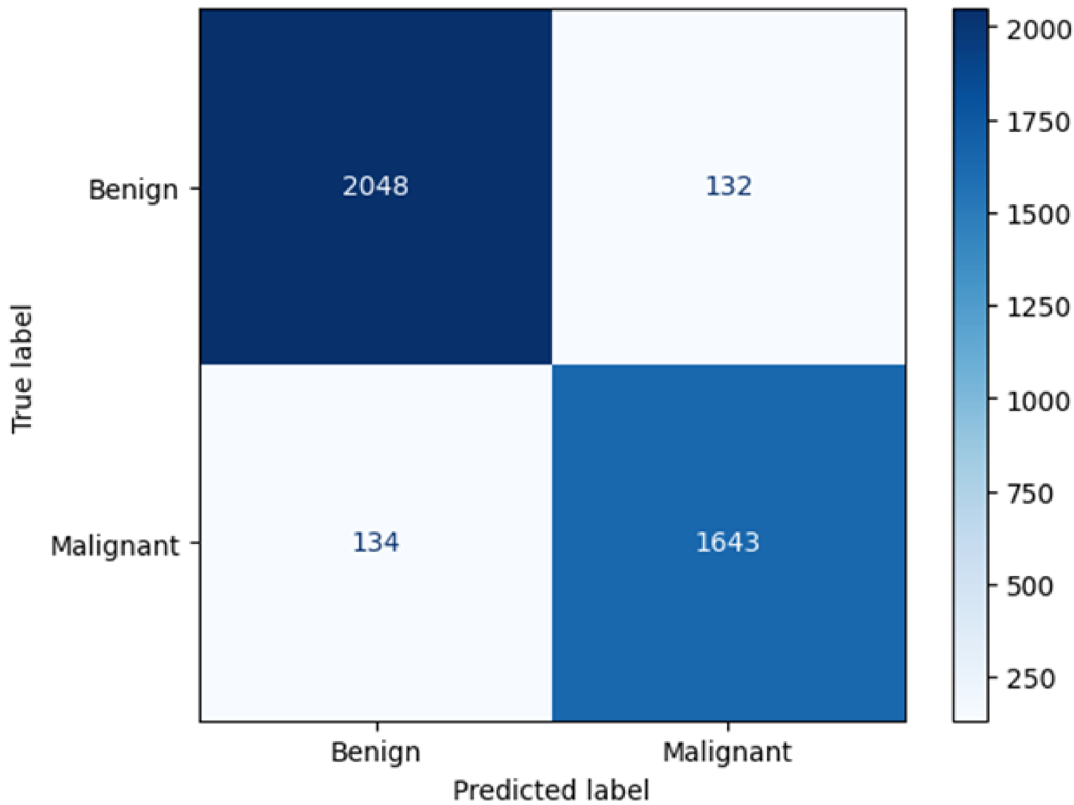

Figure 5.3: Confusion Matrix for AlexNet

5.6 SUMMARY

This chapter evaluates the performance of the implemented models using metrics like Jaccard Coefficient, Dice Coefficient, accuracy, precision, recall, specificity, and F1-score. SegNet, optimized with Genetic Algorithms, achieved the highest segmentation accuracy with a Jaccard score of 90.48% and a Dice score of 95.00%. For classification, AlexNet showed the best performance with 93.28% accuracy and an F1-score of 92.51%. Data augmentation increased the dataset size significantly, improving classification robustness. The analysis of segmentation and classification models highlights the system's reliability and precision, demonstrating its potential for clinical use in skin cancer detection.

CHAPTER 6

CONCLUSION AND FUTURE WORK

The proposed AI-based skin cancer detection system demonstrates significant advancements in early and accurate diagnosis of skin lesions by integrating deep learning techniques with optimization algorithms. Utilizing enhanced segmentation models such as SegNet optimized with genetic algorithms, the system has achieved high precision and efficiency in delineating skin lesions. The application of robust data augmentation and optimization strategies has ensured reliability across diverse datasets and clinical scenarios, enabling accurate classification of benign and malignant lesions. This system provides a valuable tool for dermatologists, aiding in reducing diagnostic errors, improving patient outcomes, and lowering healthcare costs through timely and precise detection.

Future improvements could focus on exploring hybrid deep learning architectures to enhance accuracy and robustness. Leveraging transfer learning from pre-trained models on larger and more diverse datasets could improve generalization across various skin types and conditions. Additionally, incorporating advanced optimization methods like Lion Optimizer and Sharpness-Aware Minimization (SAM) can further refine model training and performance. Real-time implementation through user-friendly diagnostic tools and integrating explainable AI techniques would enhance the system's practical applicability and trustworthiness. Expanding the dataset to include rare and diverse cases, along with conducting clinical trials, would ensure the system's comprehensiveness and readiness for real-world healthcare integration.

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