# INVESTIGATING THE IMPACT OF VARIABLE NON-LINEAR ACTIVATION FUNCTIONS ON SKIN LESION CLASSIFICATION WITH CNN

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**20951A04P4**

# INVESTIGATING THE IMPACT OF VARIABLE NON-LINEAR ACTIVATION FUNCTIONS ON SKIN LESION CLASSIFICATION WITH CNN

*A Project report*
*Submitted in partial fulfillment of the Requirement*
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**BY**

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**Under the Esteemed Guidance of**

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**DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING**

**INSTITUTE OF AERONAUTICAL ENGINEERING**

**(Autonomous)**

**Dundigal, Hyderabad-500043, Telangana April 2024**

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This is to certify that the project entitled **INVESTIGATING THE IMPACT OF VARIABLE NON-LINEAR ACTIVATION FUNCTIONS ON SKIN LESION CLASSIFICATION WITH CNN** by **Mr. B VINOD REDDY (20951A04P4)** to the **INSTITUTE OF AERONAUTICAL ENGINEERING**, Hyderabad in partial fulfillment of the requirements for the award of the Degree Bachelor of Technology in **ELECTRONICS AND COMMUNICATION ENGINEERING** is a bonafide record of work carried out by him under my guidance and supervision. The contents of this report, in full or in parts, have not been submitted to any other Institute for the award of any degree.

**Supervisor**
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**Assistant Professor**

**Head of the Department**
**Dr. P Munaswamy**

**Date :**

# APPROVAL SHEET

This project report **INVESTIGATING THE IMPACT OF VARIABLE NON-LINEAR ACTIVATION FUNCTIONS ON SKIN LESION CLASSIFICATION WITH CNN** is done by **B VINOD REDDY (20951A04P4)** is approved for the award of the Degree Bachelor of Technology in **ELECTRONINCS AND COMMUNICATION ENGINEERING.**

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I perceive this opportunity as a big milestone in my career development. I will strive to use gained skills and knowledge in the best possible way, and I will continue to work on their improvement, to attain desired career objectives. Hope to continue cooperation with all of you in the future.

With Gratitude,

B Vinod Reddy

20951A04P4

# ABSTRACT

Melanoma, a dangerous type of skin cancer, can be treated successfully if caught early. Detecting it late increases the risk of death. Melanoma starts in melanocytes, the cells that make melanin, the pigment giving color to skin, hair, and eyes. It's considered one of the most severe skin cancers because it can spread to other body parts. Skin condition is crucial in spotting diseases early. This study uses advanced computer technology called convolutional neural networks (CNNs) to better identify skin lesions. By including complex processes in the analysis, the CNN adapts well to different types of skin problems. Traditional methods like Rectified Linear Unit (ReLU) are basic and struggle with complicated shapes in skin images, so new methods like Parametric Rectified Linear Unit (PReLU), Leaky ReLU, Hyperbolic Tangent and Exponential Linear Unit (ELU) are explored. The CNN learns from a vast dataset called HAM10000, which covers many skin conditions and is labeled by skin experts. We test the CNN using sensitivity, specificity, and accuracy measures to see how well it performs compared to other methods. This research aims to make skin cancer diagnosis more accurate and accessible to everyone.

**Keywords**: Convolution neural network, HAM10000, Image augmentation, Melanoma, nonlinear activation functions

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| | |
|---|---|
| **CNN** | Convolution neural network |
| **HAM** | Human Against Machine with 10000 training images |
| **ReLU** | Rectified Linear Unit |
| **ELU** | Exponential linear unit |
| **CReLU** | Clipped ReLU |
| **LReLU** | Leaky ReLU |
| **Tanh** | Hyperbolic Tangent |
| **PReLU** | parameter ReLU |
| **TP** | True Positive |
| **TN** | True Negative |
| **FP** | False Positive |
| **FN** | False Negative |
| **SE** | Sensitivity |
| **SP** | Specificity |
| **PR** | Precision |

# CHAPTER 1

## 1.1 INTRODUCTION

Skin lesion classification is a critical task in dermatology, vital for diagnosing various skin conditions accurately and promptly. As technology evolves, Convolutional Neural Networks (CNNs) have risen as formidable assets, fundamentally transforming domains such as computer vision and pattern analysis, potent tools for this purpose, particularly in analyzing medical images like skin lesions. These networks leverage deep learning techniques to discern intricate patterns and features within dermatological images. Integrating non-linear activation functions into CNN architectures further enhances their capabilities in capturing complex information. These functions, such as Rectified Linear Unit (ReLU), Leaky ReLU, Parametric ReLU, and Exponential Linear Unit (ELU), introduce flexibility to the decision making process of the network. They allow the model to adapt to the diverse characteristics of skin lesions, facilitating effective learning and generalization across different types and stages of skin conditions.

Skin lesions exhibit vast variations in appearance, making their accurate diagnosis a challenging task for traditional image processing techniques. CNNs, inspired by the human brain's visual processing capabilities, excel in image classification tasks by automatically learning hierarchical representations of features from input images. The inclusion of convolutional layers enables these networks to capture and understand complex spatial relationships within the images, which is crucial for accurate classification.

This research endeavors to explore the synergies between CNNs and non-linear activation functions in the context of skin lesion classification. By studying the impact of different activation functions at various layers of the network, we aim to optimize the model's performance, enhance its interpretability, and overcome challenges associated with traditional approaches. Ultimately, our goal is to improve the accuracy and efficiency of skin lesion classification, thereby contributing to better healthcare outcomes for patients.

In HAM10000 (Human Against Machine with 10000 training images) a huge collection of multi-source dermatoscopic images of pigmented lesions having seven types of skin diseases. They are shown in Fig 1.1.

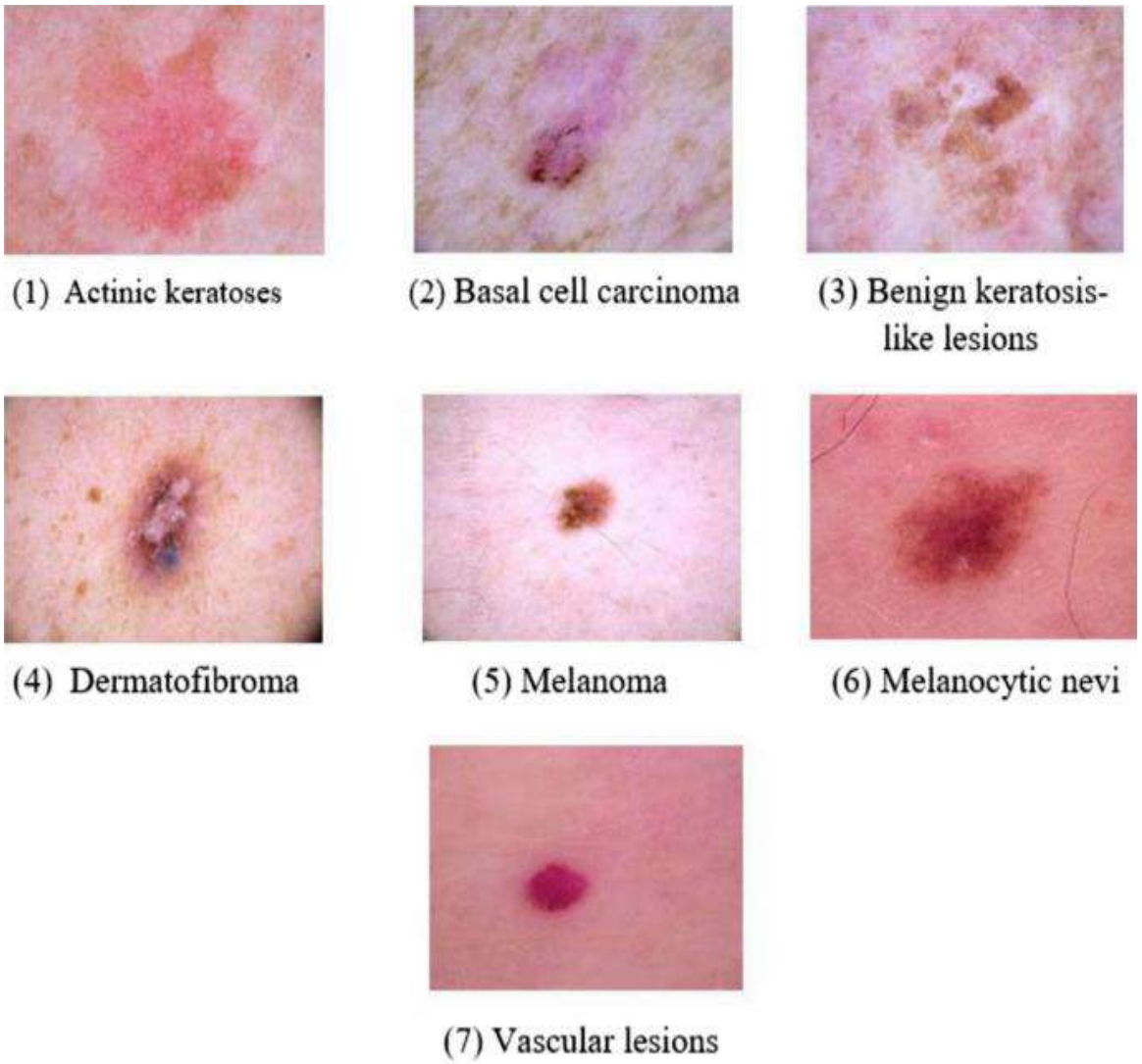



**Fig 1.1: Seven Types of Skin Cancer Images**

Where as HAM10000 dataset is unbalanced in image count and they are shown in the Fig1.2. In Fig 1.2 it is machine generated count of individual skin cancers. We use the method augmentation to balance or oversampling the images

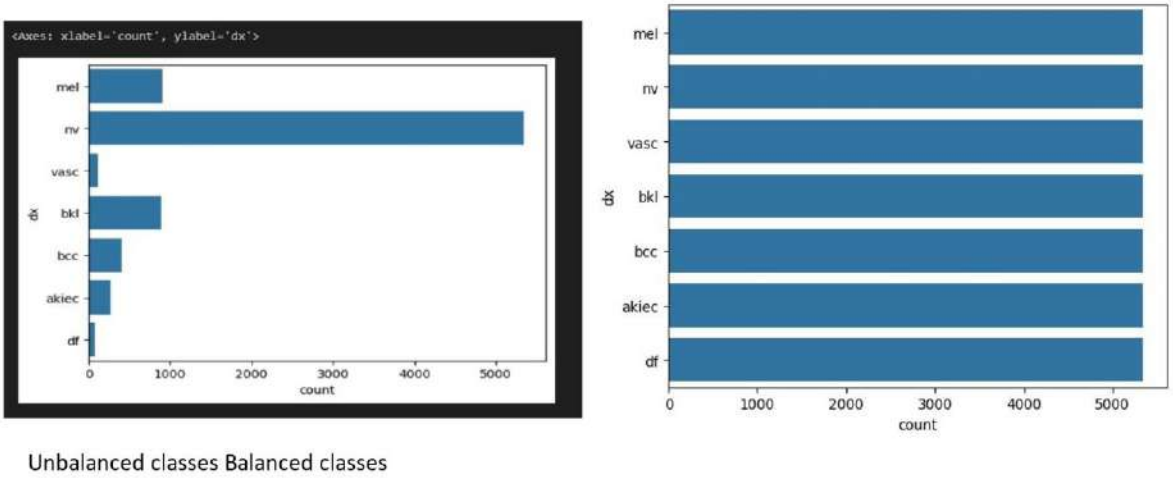



**Fig 1.2: Data Augmentation**

**RANDOME IMAGES FROM DATASET:**

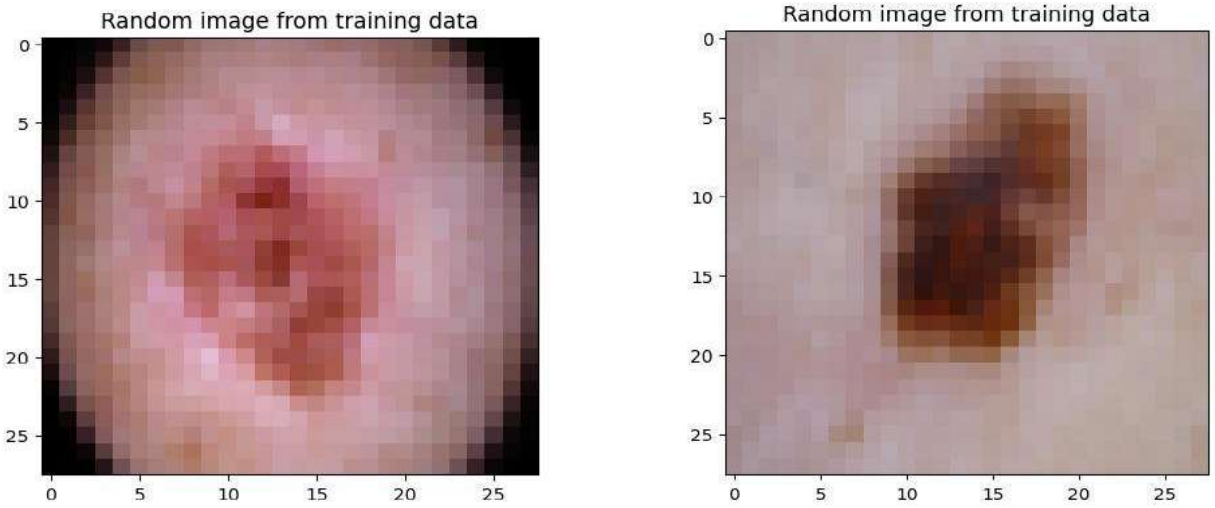



**Fig 1.3:** some random images after balanced

## 1.2 Real Time Applications:

The real-time application of Convolutional Neural Network (CNN)-based skin lesion

classification using variable non-linear activation functions can have several practical use cases in the field of dermatology and healthcare. Here are some scenarios where such a system could applied

**Automated Dermatology Diagnosis:**

Provide automated and rapid skin lesion classification for dermatologists, enabling quicker and more efficient diagnosis. The system can assist healthcare professionals by quickly identifying potential malignant or benign lesions, aiding in early detection and treatment.

**Telemedicine and Remote Consultations:**

Facilitate telemedicine applications by allowing patients to capture images of their skin lesions using smartphones or dedicated devices. The CNN model, with variable non-linear activation functions, can analyze these images in real-time, providing preliminary assessments for remote consultations.

**Dermoscopy Assistance:**

Support dermatoscopists in analyzing dermoscopic images, which are magnified and illuminated images of skin lesions. The CNN model can assist in recognizing patterns indicative of different skin conditions, contributing to accurate diagnosis.

**Skin Cancer Screening Clinics:**

Implement the system in screening clinics for early detection of skin cancer. Patients can undergo a quick imaging session, and the CNN model can rapidly classify lesions, aiding in prioritizing patients who may require further examination.

**Mobile Applications for Self-Examination:**

Develop mobile applications that allow individuals to conduct self-examinations by taking pictures of their skin lesions. The CNN model can then provide instant feedback on the likelihood of the lesion being benign or malignant, encouraging users to seek professional medical advice.

## 1.3 Objectives:

Objective 1: Improve Classification Accuracy

Objective 2: Explore Variable Non-Linear Activation Functions

Objective 3: Optimize Model Generalization

Objective 4: Enhance Model Robustness

Objective 5: Facilitate Interpretability

Objective 6: Adaptability to Variable Activation Functions

Objective 7**:** Mitigate Overfitting

Objective8: Contribute to Clinical Decision Support

## 1.4 Overview

A Deep Learning based approach for Convolution Neural Network based Skin cancer Classification with Variable non linear Activation Functions involves the use of advanced Convolution neural network architectures to automatically identify and delineate skin cancer from HAM10000 Dataset. This process is crucial for various applications, including disease diagnosis, treatment planning, and medical research. Here's an overview of the key components and steps involved in such an approach:

**1. Data Collection and Preprocessing:**

Dataset Compilation: Gather a diverse and representative dataset of skin lesion

Data Augmentation: In Data Augmentation some techniques such as rotation, flipping, and scaling to augment the

dataset and enhance model robustness. As shown in Fig 1.3.

**2. Model Architecture:**

Convolutional Neural Networks (CNNs): Utilize deep learning architectures, especially CNNs,

known for their effectiveness in image-related tasks. As shown in Fig 1.3.

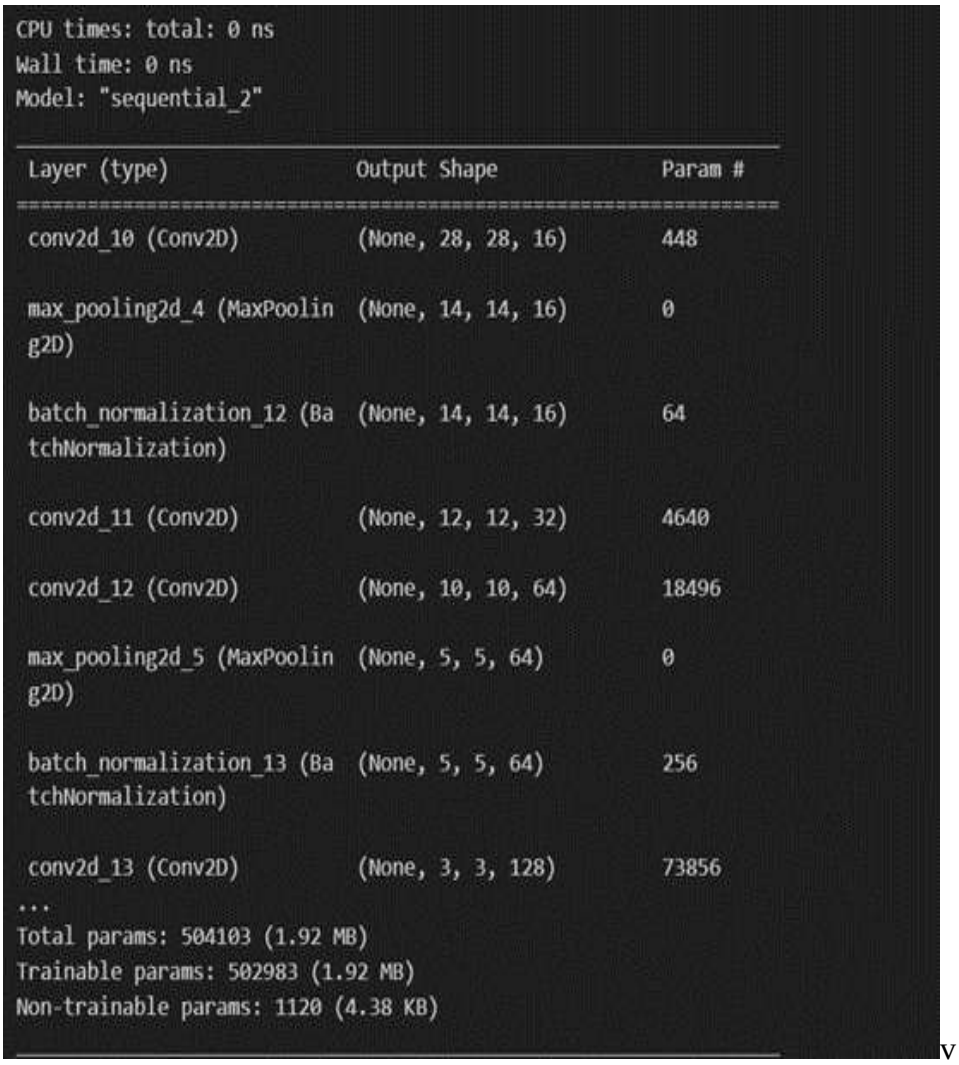



**Fig 1.4: CNN Architecture**

**3. Training:**

Loss Functions: Employ appropriate loss functions, such as binary cross-entropy or a combination with Dice loss, to guide the model during training.

Optimization: Use optimization algorithms like Adam to minimize the loss function and adjust model parameters.

**4. Validation and Testing:**

Cross Validation: Evaluating the model's performance using cross-validation techniques to ensure

generalizability.

Testing: Assess the model on an independent test set to validate its effectiveness in skin detection accurately

# CHAPTER 2
# LITERATURE SURVEY

Skin disorders present significant challenges in early detection and classification due to various factors such as subtle symptoms, limited access to dermatologists, and imaging difficulties. To address this, we propose a clinical decision support model called DermCDSM, which integrates an improved division process using an enhanced chameleon swarm optimization (ICSO) method for accurate disease identification. Additionally, the multi-strategy seeking optimization (MSSO) algorithm aids in feature selection to handle data dimensionality challenges. Implementing convolutional deep spiking neural networks (CD-SNN) enhances precision in skin cancer diagnosis and classification. Validated on the ISIC 2017 dataset, DermCDSM demonstrates superior accuracy, reliability, and efficiency compared to existing methods, showcasing its potential to improve skin disease diagnosis and classification.[1]

Skin cancer is a significant concern globally, with early detection crucial for improving survival rates. Traditional methods like dermoscopy have limitations, prompting researchers to explore new approaches. In this study, a novel method incorporating hand-crafted features derived from image, spectrogram, and cepstrum domains, alongside a 1-D multi headed CNN, showed promising results. By leveraging both spatial and spectral information, the proposed model achieved high accuracies on challenging datasets like HAM10000 and Dermnet. These findings suggest a potential for enhancing clinical diagnosis accuracy, offering a valuable tool in the fight against skin cancer.[2]

Skin cancer is rapidly becoming a prevalent global health concern, compounded by limited resources available for its management. Early detection is paramount for accurate diagnosis and preventive measures. However, identifying skin cancer at its nascent stage poses challenges for dermatologists. In recent years, advancements have been made in both supervised and unsupervised learning approaches, particularly deep learning, have gained prominence in this domain. Among these, Convolutional Neural Networks (CNNs) have emerged as the most effective models for object detection and classification tasks. For experimentation, a dataset sourced from MNIST: HAM10000, containing seven distinct types of skin lesions and comprising

10,015 samples, was utilized. Prior to training the model, data preprocessing techniques such as sampling, refinement using autoencoder and decoder for segmentation, were employed to enhance the quality of the dataset. Additionally, transfer learning methods, including DenseNet169 and ResNet50, were applied to train the model and generate results. This approach leverages the power of deep learning and transfer learning techniques To enhance the precision and effectiveness of skin cancer detection. This approach is employed utilizing advanced methodologies and a comprehensive dataset, this research aims to contribute to the early detection and management of skin cancer, ultimately reducing its impact on public health. [3]

In the realm of dermatology, the early detection of skin cancer poses significant challenges. Our research concentrated on employing various datasets, encompassing original, augmented, and SMOTE oversampled data, to discern skin cancer. The dataset was comprised of images depicting skin lesions sourced from the MNIST Skin Cancer dataset (HAM 10000), encompassing both cancerous and benign cases. To augment the dataset's size and enrich the diversity of skin lesion attributes, we implemented data augmentation techniques. Moreover, in order to address class imbalance within the dataset, we utilized the SMOTE oversampling method to generate synthetic samples for the under-represented category. Utilizing the original, augmented, and SMOTE oversampled datasets, we proceeded to train a Convolutional Neural Network (CNN) model. The performance of the model was assessed through metrics such as accuracy, recall, precision, and F1-score. Upon comparison of the outcomes obtained from the original, augmented, and SMOTE oversampling datasets, notable disparities in performance were evident. Our research unequivocally demonstrates that the integration of data augmentation and SMOTE oversampling techniques can substantially bolster the effectiveness of skin cancer detection processes. By leveraging these methodologies, we aim to contribute to the advancement of early detection techniques in dermatological practices, thereby enhancing patient outcomes and overall healthcare efficacy. [4]

Skin cancer represents a widespread malignancy globally, emphasizing the crucial importance of its early and precise diagnosis for patient survival. However, clinical evaluation of skin lesions encounters obstacles such as extended wait times and subjective interpretations. To address these challenges, deep learning techniques have been developed to aid dermatologists in achieving more accurate diagnoses. Timely

treatment of skin cancer is paramount in halting its progression and averting potentially life-threatening outcomes. Deep learning algorithms offer a promising avenue for enhancing the speed and accuracy of diagnosis, facilitating earlier detection and intervention. Moreover, they alleviate the burden on healthcare professionals, allowing them to focus on more intricate cases. This study aimed to develop dependable deep learning (DL) prediction models for skin cancer classification, addressing the prevalent issue of severe class imbalance where affected skin patients' class significantly outnumber the healthy class. Additionally, the study sought to interpret model outputs to gain insights into the decision-making mechanism and proposed an End-to-End smart healthcare system via an Android application. By comparing the effectiveness of the proposed DL technique with six established classifiers, the study assessed metrics related to both generalization capability and classification accuracy. Utilizing the HAM10000 dataset, an optimized convolutional neural network (CNN) was trained to identify the seven forms of skin cancer. The model underwent training with two optimization functions (Adam and RMSprop) and three activation functions (Relu, Swish, and Tanh) to explore various performance metrics. [5]

Recent advancements in deep neural network-based methods have shown significant promise in accurately identifying skin lesions from dermoscopic images. However, many existing approaches primarily focus on enhancing network frameworks to improve feature representation, neglecting the critical issue of data imbalance. This oversight hampers their adaptability and accuracy, particularly in multi-center clinic settings where varying data distributions pose challenging requirements. Addressing this, our paper shifts focus from framework enhancement to tackling data imbalance, presenting a novel solution for multi-center skin lesion classification. We introduce an innovative adaptively weighted balance (AWB) loss to conventional classification networks. The AWB approach offers several advantages: 1) it facilitates easy adaptation to diverse practical requirements by simply modifying the network backbone; 2) it is user-friendly, requiring no hyperparameter tuning; and 3) it adaptively adjusts intraclass

compactness, prioritizing the minority class. Extensive experiments demonstrate that our proposed solution outperforms solutions equipped with state-of-the-art loss functions. It exhibits greater flexibility and competence in addressing multi-center imbalanced skin lesion classification tasks, achieving notable performance improvements on two benchmark datasets. Furthermore, our solution proves effective in handling imbalanced tasks beyond skin lesion classification, including imbalanced gastrointestinal disease classification and diabetic retinopathy grading tasks. This research marks a significant step towards enhancing the adaptability and accuracy of deep learning-based methods in clinical settings with varying data distributions. [6]

Skin cancer, one of the deadliest cancer forms, has seen increasing mortality rates due to insufficient awareness regarding symptoms and preventative measures. Timely detection plays a pivotal role in halting its progression. Given the various types of skin cancer, especially those with pigmentation, advanced image detection techniques and computer classification capabilities are essential. In our model, we utilize the HAM10000 dataset, comprising 10,015 images, to bolster skin cancer detection accuracy. Through meticulous dataset selection and augmentation techniques, we refine the model's precision. Our focus lies primarily on a CNN-based model, which achieves an impressive validation accuracy of 97.92%. This research makes significant strides in early identification of specific skin disease categories, facilitating prompt validation and treatment administration by medical professionals.[7]

Early identification of melanoma is vital for improving the likelihood of successful treatment. To address this, the study initiates with a comprehensive review of existing methodologies employed in skin cancer classification. Our chosen approach involves the utilization of Convolutional Neural Networks (CNNs) for the identification and diagnosis of skin cancer, utilizing the IS IC dataset comprising 2637 images. The developed model demonstrates promising results, achieving an accuracy of 88% in distinguishing between benign and malignant lesions within the training dataset. This methodology integrates state-of-the-art machine learning techniques to enhance the accuracy and efficiency of melanoma detection. By leveraging CNNs, which are adept

at learning intricate patterns within images, our model provides a robust framework for early diagnosis, facilitating timely interventions and improving patient outcomes. Additionally, the extensive literature survey ensures that our methodology is informed by a thorough understanding of existing approaches, allowing for meaningful contributions to the field of skin cancer classification. Overall, this research presents a promising avenue for enhancing early melanoma detection through advanced machine learning techniques and comprehensive analysis.[8]

Non-linear activation functions are essential in deep neural networks for training and classification tasks. Despite numerous proposals for such functions in recent years, many exhibit shortcomings, leading to inefficiencies in deep neural network models. Common issues include vanishing gradients, dying neurons, and gradient explosions. To address these challenges, this study introduces a novel activation function named SaRa (Swish and ReLU Activation), which combines features of the Swish and ReLU functions. The performance of this new activation function is evaluated using a transfer learning-based Convolutional Neural Network (CNN) model on the ISIC archive dataset for melanoma skin cancer classification. Results demonstrate that the SaRa activation function surpasses other activation functions in terms of training validation and classification performance. This innovative approach not only mitigates the limitations associated with traditional activation functions but also enhances the efficiency and effectiveness of deep neural network models, particularly in tasks like melanoma skin cancer classification. [9]

Skin cancer has emerged as a significant health concern in recent times, with melanoma, basal cell carcinoma, and squamous cell carcinoma posing serious threats. Among these, melanoma is particularly concerning due to its potential severity. Early detection significantly improves the prognosis of melanoma. Leveraging computer vision in medical imaging has shown promise in various systems. This study focuses on utilizing machine learning and advanced technological tools to identify melanoma skin cancer. The process involves submitting a skin lesion image to the system, which employs novel image processing algorithms to analyze it for signs of cancer. By segmenting the image and assessing factors like texture, size, and shape, the system detects the presence of melanoma. Utilizing derived feature characteristics, the lesion image is then classified as either a malignant lesion, normal skin, or melanoma. In summary, DermaGenics is a web application featuring the YOLOv5 model, enabling

users to input images of skin lesions for evaluation. The model efficiently determines whether the lesion is cancerous or benign, enhancing early detection and treatment. [10]

Melanoma (MEL) is a severe type of skin cancer with significant health ramifications. Early and precise analysis of MEL is vital for optimizing treatment effectiveness. Utilizing Computer Vision Systems (CVS), this study proposes an automated method to detect and classify various skin cancer diseases by processing dermatoscopic images. Deep Learning (DL) techniques, with TensorFlow backend and Keras libraries, are employed. The study employs the HAM-10000 dataset, comprising 10,015 dermoscopic images, allocating 70% for training, 24% for testing, and 6% for model validation. Pre-processing steps include converting images to grayscale to remove noise and hair, followed by database enhancement techniques like thresholding, morphological filtering, Black Hat, and Inpaint. Data augmentation via TensorFlow and Keras improves the training dataset's size and quality. Classification utilizes the MobileNet optimizer. The proposed method demonstrates advanced diagnosis and classification accuracy compared to previous techniques. Performance is validated using Top-N accuracy metrics, achieving a Top-1 accuracy of around 90%. With a Top-1 precision of 90%, this study surpasses the benchmark, highlighting its high classification efficiency and speedy outcomes delivery. [11]

Melanoma, a severe form of skin cancer, exhibits higher curability rates when diagnosed early, underscoring the importance of timely detection. Delay in identifying lesions directly correlates with increased mortality risk. A Deep Learning-powered computer diagnostic system offers an automated solution for clinical assessments, aiding in early detection. Convolutional Neural Networks (CNNs) facilitate improved classification of skin lesions from dermoscopic images, eliminating the need for human intervention. Linear and nonlinear activation functions within CNNs serve as decision-making nodes, influencing information passage between layers and ultimately impacting accuracy. However, CNNs necessitate substantial training data for optimal performance. This study investigates the efficiency of different nonlinear activation functions in CNNs using limited image datasets. Experimental findings indicate that a CNN model incorporating parameterized Leaky ReLU function achieves superior performance (97.50% accuracy, 98.00% precision, and 98.00% sensitivity) compared to models employing alternative nonlinear activation functions. The research focuses on melanoma recognition, categorizing skin lesions into three classes. All experiments are conducted

using images from the PH2 and International Skin Imaging Collaboration (ISIC) archive datasets. By demonstrating the efficacy of specific activation functions in CNNs with constrained datasets, this study contributes to advancing the accuracy and efficiency of melanoma diagnosis through computational methods. [12]

Melanoma, known as the deadliest skin cancer type, poses a considerable challenge in distinguishing its lesions from non-melanoma lesions. Previous Computer-Aided Diagnosis and Detection Systems have encountered difficulties due to the intricate visual characteristics of skin lesion images, characterized by uneven textures and blurred boundaries. In this study, we propose a deep learning-based approach to overcome these challenges for automatic melanoma lesion detection and segmentation. Our method involves an improved encoder-decoder network architecture, integrating encoder and decoder sub-networks via skip connections to harmonize the semantic levels of feature maps, thereby facilitating efficient learning and feature extraction. Employing a multi-stage, multi-scale strategy, our system utilizes a softmax classifier for pixel-wise classification of melanoma lesions. Additionally, we introduce a novel method called Lesion-classifier, which categorizes skin lesions as melanoma or non-melanoma based on pixel-wise classification results. Experimentation on two well-established skin lesion datasets, the International Symposium on Biomedical Imaging (ISBI) 2017 and Hospital Pedro Hispano (PH2), showcases the effectiveness of our approach compared to state-of-the-art techniques. We achieved an accuracy and dice coefficient of 95% and 92% on the ISIC 2017 dataset, and an accuracy and dice coefficient of 95% and 93% on the PH2 dataset, respectively. These findings underscore the potential of our method in improving the accuracy and efficacy of automatic melanoma lesion detection and segmentation. [13]

Skin cancer incidence is increasing annually, partly due to ozone layer depletion allowing more ultraviolet radiation to reach the Earth's surface. Consequently, there's a growing demand for simple image processing methods to aid in early skin cancer detection. Research in this area intensified following the release of a large skin cancer image dataset by ISIC in 2016. While previous studies relied on complex hand-crafted image processing combined with machine learning, this approach proved challenging. This study investigates the impact of a simpler technique: contrast enhancement using CLAHE and MSRCR, along with CNN. Results indicate that CLAHE is more effective than MSRCR in enhancing color images for early skin cancer detection using CNN. Surprisingly, both the original and CLAHE-enhanced datasets yield identical accuracy

rates in training and validation. A significant finding is that image contrast enhancement may not be crucial for skin cancer screening. This study emphasizes the importance of evaluating and refining image processing techniques for efficient and accurate early skin cancer detection. [14]

Melanoma stands out as the most dangerous type of skin cancer, prompting a shift towards Convolutional Neural Network (CNN) based classifiers for its detection. Recent research has shown that CNN classifiers perform comparably to dermatologists, facilitating rapid and life-saving diagnoses. This study undertakes a systematic literature review focusing on the latest advancements in melanoma classification using CNN. Specifically, the research centers on binary classification of melanoma lesions. The examination delves into various CNN classifiers and evaluates their accuracies when applied to unpublished datasets. The review process involved a comprehensive search across prominent databases including IEEE, Medline, ACM, Springer, Elsevier, and Wiley, yielding a pool of 5112 studies. From this pool, 55 well-regarded studies were meticulously selected for analysis. The primary aim of this study is to synthesize cutting-edge research, shedding light on emerging trends, challenges, and opportunities in melanoma diagnosis while exploring deep learning-based solutions for melanoma detection. Furthermore, the study introduces a proposed taxonomy for melanoma detection, providing a comprehensive overview of existing methodologies. Additionally, it presents a model outlining current challenges and future opportunities in the realm of melanoma detection, serving as a valuable resource for researchers in the field. This systematic review not only consolidates state-of-the-art research but also offers insights into the evolving landscape of melanoma diagnosis, paving the way for advancements in early detection and treatment. [15]

**Table 2.1**: some author with models and accuracy

| authors | year | model | Activation functiomin hidden layers | No.of datasets | No.of training images | SE% | AC% |
|---|---|---|---|---|---|---|---|
| S.Kadry | 2022 | VCCGG-segnet | ReLU | 1 | 1,250 | 95 | 96 |
| Khan | 2021 | CNN | ReLU | 1 | 10015 | 92 | 95 |
| YU | 2017 | FCRN | CReLU | 1 | 1250 | 90 | 91 |
| Khan | 2021 | DenseNet | ReLU | 3 | 14,044 | 96 | 96 |
| Polap | 2019 | CNN | TANH | 2 | 273 | 81 | 82 |
| Mabbod | 2019 | CNN | ReLU | 2 | 2187 | 91 | 91 |
| Harangi | 2018 | CNN | PReLU | 1 | 14300 | 56 | 87 |

Table 2.1 presents a comparison of various authors' models along with their respective accuracies. S.Kadry's VCCGG-segnet model from 2022 utilized ReLU activation function in hidden layers, achieving an accuracy of 96% on a dataset comprising 1,250 images. Khan's CNN model from 2021, employing ReLU activation function, attained a 95% accuracy with a dataset containing 10,015 images. YU's FCRN model from 2017 utilized CReLU activation function, achieving a 91% accuracy with 1,250 images. Khan's DenseNet model from 2021, using ReLU activation function in three layers, achieved a remarkable 96% accuracy with 14,044 images. Polap's CNN model from 2019, employing TANH activation function in two layers, achieved an accuracy of 82% with 273 images. Mabbod's CNN model from 2019, utilizing ReLU activation function in two layers, attained a 91% accuracy with 2,187 images. Finally, Harangi's CNN model from 2018, incorporating PReLU activation function, achieved an accuracy of 87% with a dataset containing 14,300 images. These results showcase the performance and effectiveness of different models and activation functions in image classification tasks.

## 2.1 EXISTING SOLUTION:

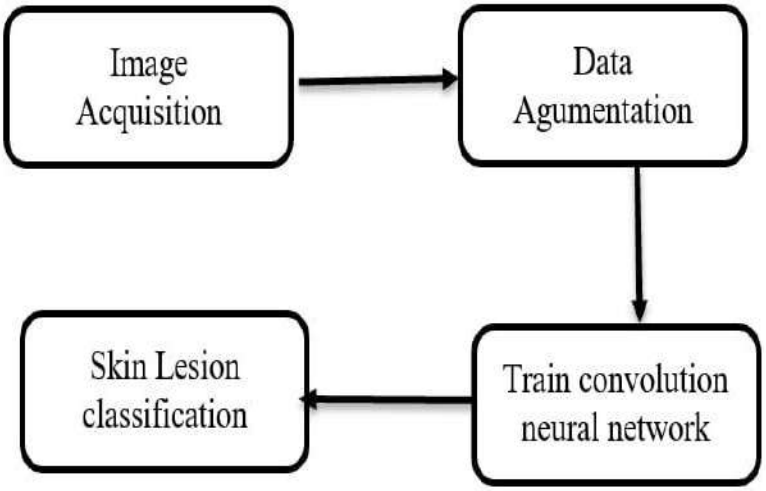



**Fig2.2:** Existing Flowchart

**Image Acquisition**

The dataset used to train a deep convolutional neural network (CNN) for lesion classification comprises 10,015 high-resolution images depicting various types of skin diseases. These images were sourced from the HAM10000 database, which is a collaborative effort between Universidade do Porto, Instituto Superior Tecnico Lisboa, and the Dermatology Service of Hospital Pedro Hispano in Matosinhos, Portugal.

All images were captured under consistent conditions using the Tubingen Mole Analyzer process, with a magnification of 20 times. Each image is represented as an 8-bit RGB format with a resolution of 768 × 560 pixels. The dataset is categorized into three classes: Atypical Nevus, Common Nevus, and Melanoma, as illustrated in Figure 2.2.

This dataset provides a valuable resource for training and evaluating deep learning models aimed at automated skin lesion classification, which is crucial for early detection and diagnosis of skin diseases such as melanoma. The standardized acquisition process and diverse representation of skin conditions enhance the robustness and generalization capabilities of the trained models.

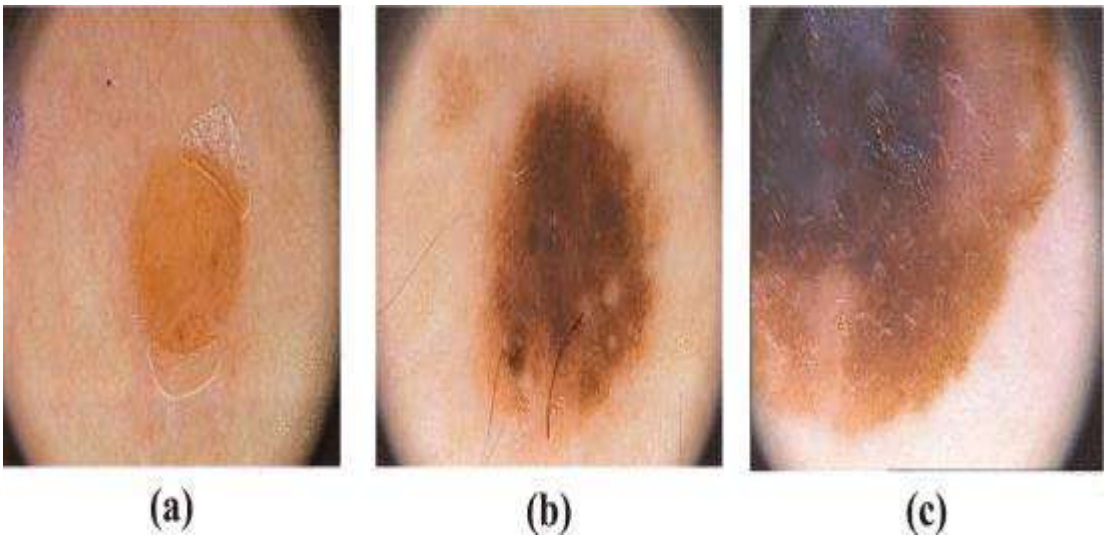



**Fig 2.3.** (a) Common Nevus, (b) Atypical Nevus, and (c) Melanoma.

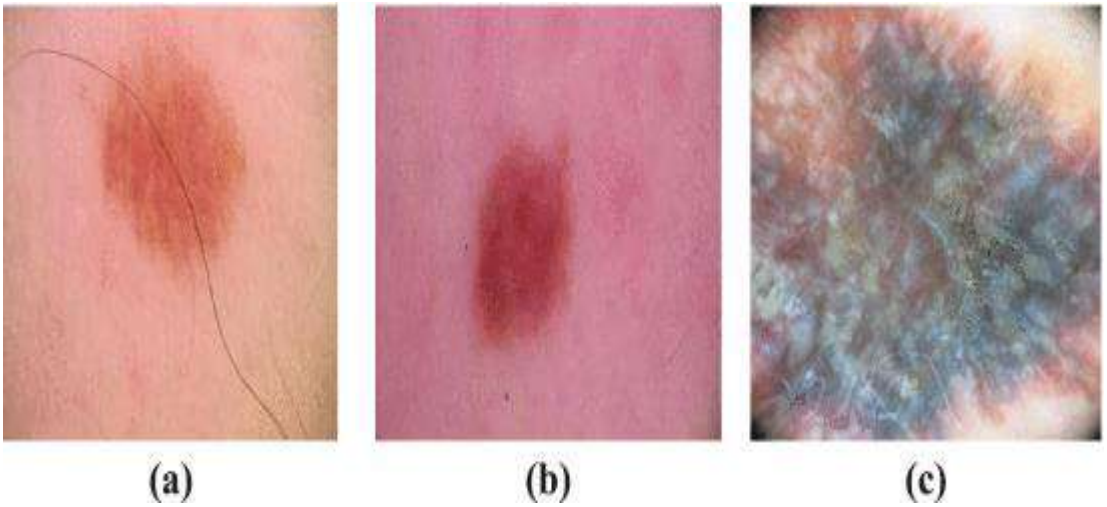



**Fig 2.4.** (a) Benign, (b) Nevus, and (c) Melanoma.

**Data Augmentation**

To enhance the training dataset and improve the CNN model's performance, augmentation techniques were applied to the HAM10000 dataset. Since the original dataset contained only 10,015 images across seven classes—1257 Melanoma, 5648 Common Nevus, and 2475 Atypical Nevus—the training accuracy of the proposed CNN model was not satisfactory.
To address this limitation, rotation augmentation was employed. Common Nevus and Atypical Nevus images were rotated by 180 degrees, effectively doubling the number of training samples in each class from 80 to 160 and 40 to 80, respectively. Similarly, Melanoma images were also rotated by 180 degrees to increase the number from 40 to 80 images.
The resulting augmented dataset, termed the augmented HAM10000 dataset, comprised 400

images in total. This augmentation strategy aimed to maximize training data while maintaining the diversity of samples within each class. Importantly, these rotation techniques were selected as they effectively increased dataset size without introducing additional complexities or requiring extensive computational resources. In Figure 2.5, (a) and (b) depict the original and augmented Common Nevus images, respectively. Similarly, in Figure 2.6, (a) and (b) represent the original and augmented Atypical Nevus images. Lastly, in Figure 2.7, (a) and (b) correspond to the original and augmented Melanoma images, respectively. These augmentation efforts align with the research goal of training the CNN model with a minimum number of images while enhancing its performance and generalization capabilities.

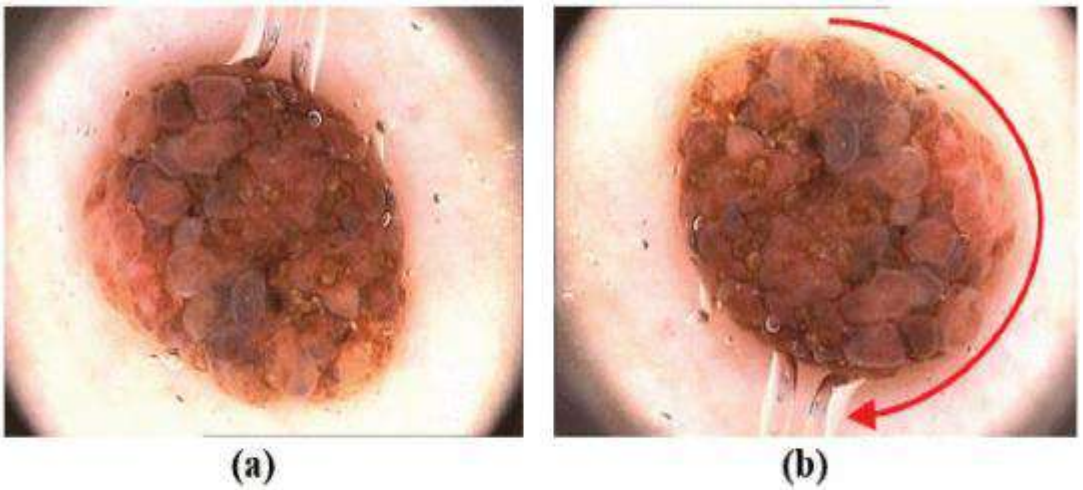



**Fig2.5.** (a) Original, and (b) 180 degree rotated Common Nevus.

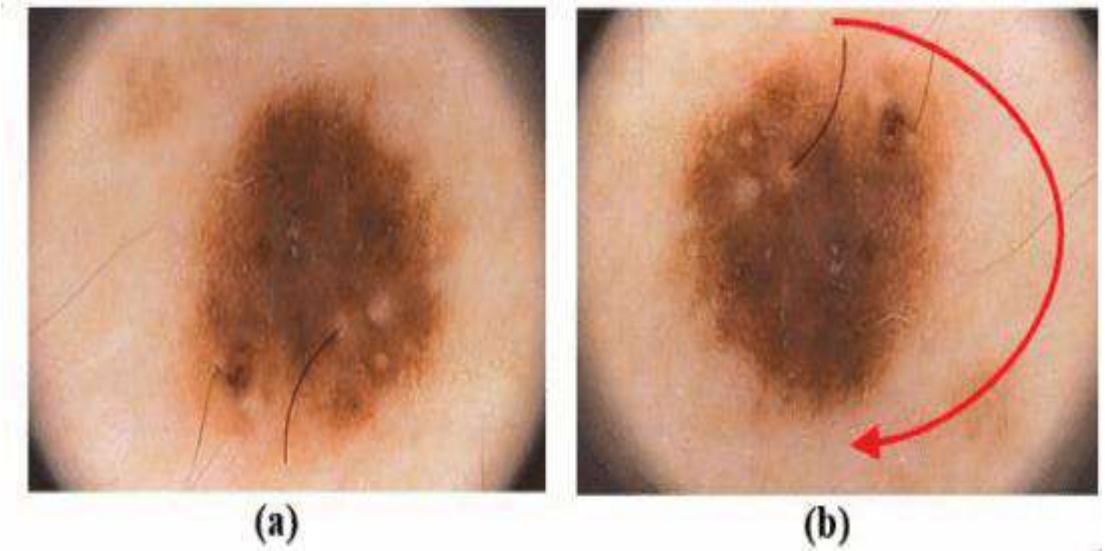



**Fig2.6.** (a) Original, and (b) 180 degree rotated Atypical Nevus.

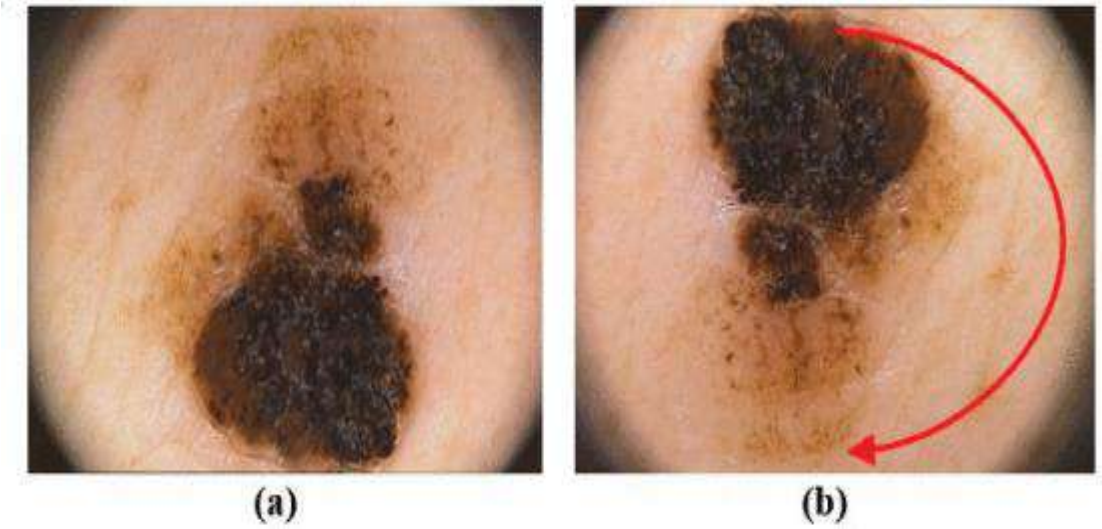



**Fig 2.7.** (a) Original, and (b) 180 degree rotated Melanoma.

**Existing Convolutional Neural Network**

The block diagram in Figure X illustrates the comprehensive workflow from image preprocessing to feature extraction and skin lesion classification. The proposed CNN architecture is founded on the principles of deep neural network design, incorporating essential components such as 2D convolution, batch normalization, activation functions, and max-pooling layers. Key insights from LeNet, originally devised for handwritten digit recognition, serve as foundational inspiration for the proposed design. The initial CNN architecture consists of three convolutional layers, two pooling layers, and three fully-connected layers. Despite this baseline design, the achieved results fall below expectations. Consequently, various parameters including stride, dilation factor, maximum epochs, convolutional filter size, and max-pooling filter size undergo iterative adjustments to identify the optimal combination for the proposed model. Multiple rounds of testing and training are conducted to fine-tune these hyperparameters, ensuring consistency across different activation functions explored during the experimental phase.

This systematic approach aims to optimize model performance and enhance its ability to accurately classify skin lesions. By refining the CNN architecture and meticulously adjusting hyperparameters, the proposed model seeks to achieve superior classification accuracy, thereby advancing the capabilities of automated skin disease diagnosis.

## 2.2 PROPOSED SOLUTION:

This flowchart is depicting the implementation Creating a flowchart for a Convolutional Neural Network (CNN) based skin cancer classification with variable non-linear activation functions. Thus the process begins.

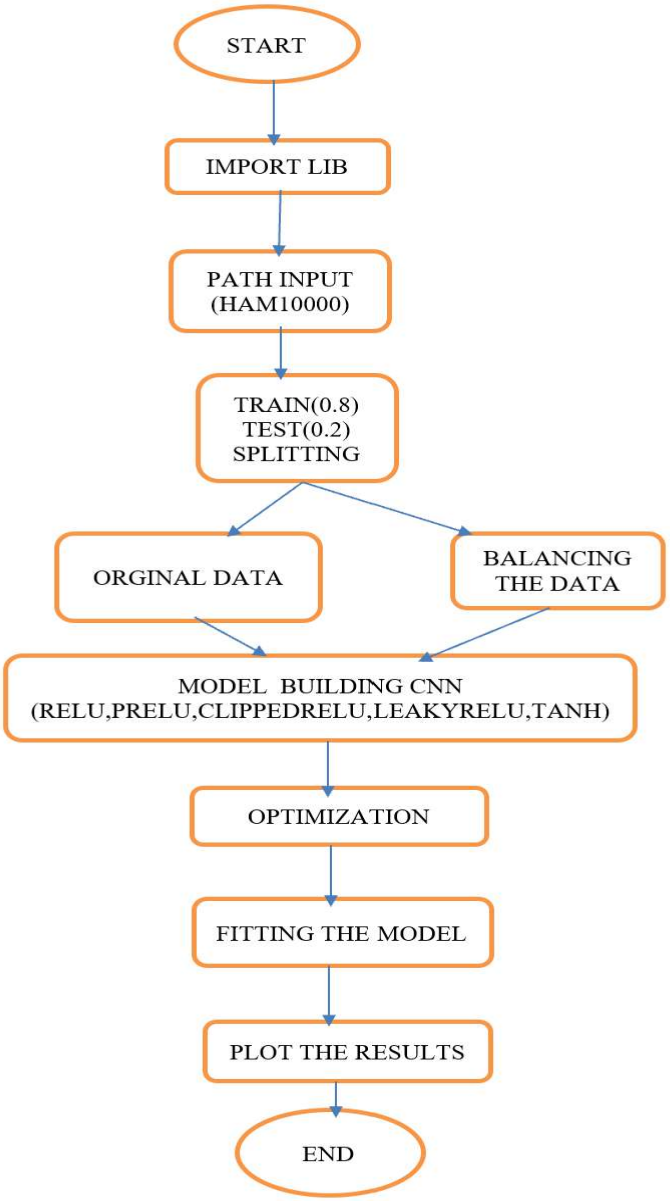



Fig: 2.8 proposed flowchart (Algorithm)

# CHAPTER 3

# METHODOLOGY

## 3.1 PROPOSED BLOCK DIAGRAM:

This Block Diagram is depicting the implementation Creating a flowchart for a Convolutional Neural

Network (CNN) based skin lesion classification with variable non-linear activation functions. Thus the process begins.

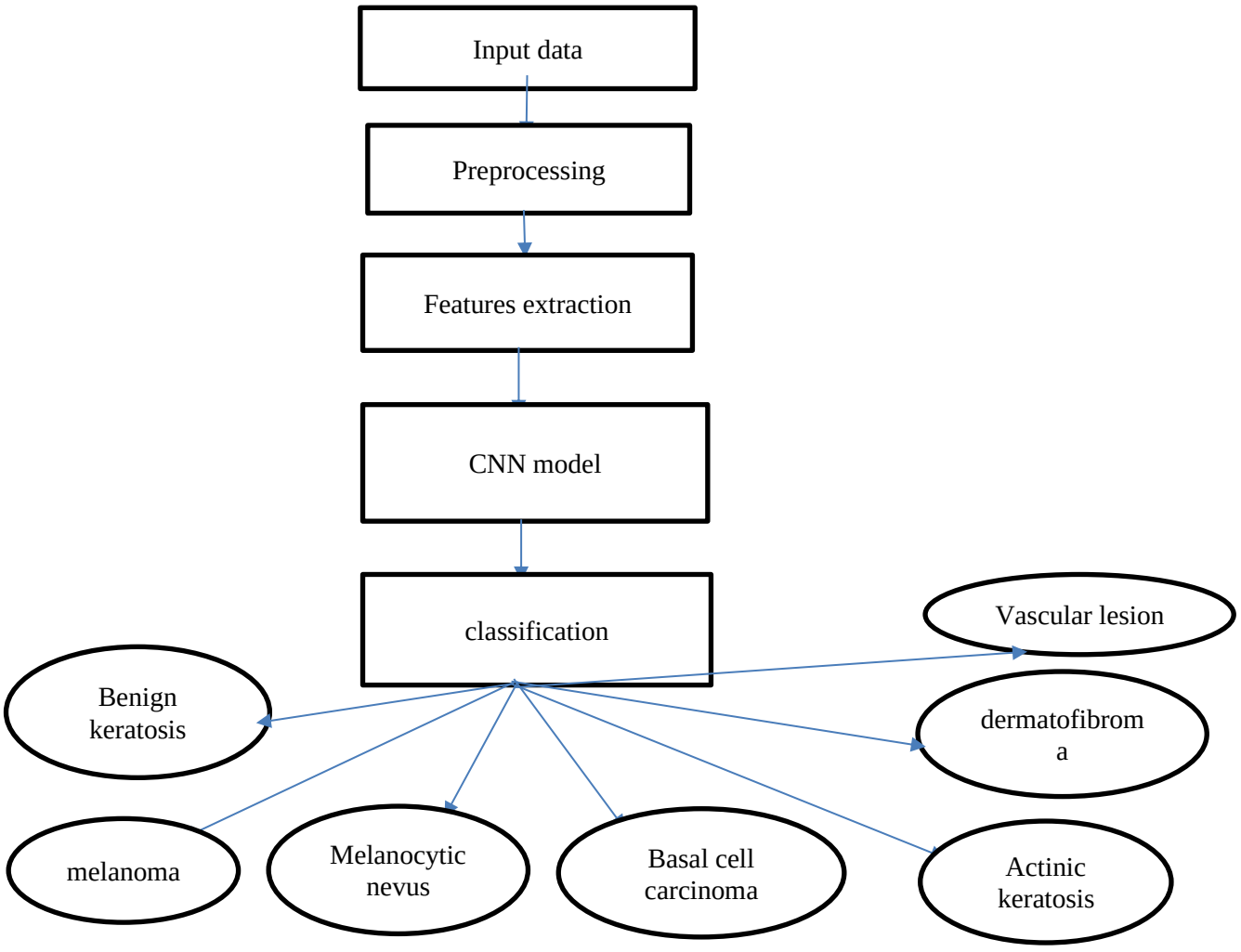



Fig: 3.1 Block Diagram

## 3.2 LIBRARIES USED:

When developing a skin lesion detection model using deep learning, several popular libraries and frameworks can be used to streamline the process. Here are some commonly used libraries in the context of skin cancer detection.

**NumPy:**

NumPy stands as a cornerstone package for scientific computation within Python. It offers robust support for handling extensive, multi-dimensional arrays and matrices, making it indispensable for a wide range of numerical computing tasks making it essential for data manipulation and numerical operations.

**Tensor flow:**

TensorFlow is an open source deep learning library developed by Google. It provides tools for building and training neural network models, making it widelyused in the deep learning community.

**Pandas:**

Pandas is a data manipulation library in Python that is commonly used for handling and analyzing structured data. It can be useful for managing datasets andpreparing data for training.

**Matplotlib and seaborn:**

Matplotlib and Seaborn are visualization libraries in Python. They can be used for plotting graphs and visualizing the performance of the model, such as ROCcurves, confusion matrices, and training/validation curves.

**Pillow:**

Pillow is a fork of the Python Imaging Library (PIL) and is used for image processing tasks. It can be useful for loading, manipulating, and saving image data.

**Open CV:**

OpenCV (Open Source Computer Vision Library) is a powerful computer vision library that can be used for image processing and analysis. It is often used forimage preprocessing and augmentations in skin cancer detection tasks.

**Keras:**

Keras is an open-source high-level neural networks API written in Python and capable of running on top of TensorFlow. It provides a user-friendly interface for building and training deep learning models.

**Pytorch:**

PyTorch is another popular open-source deep learning library. It is known for its dynamic computation graph and is widely used in both research and industry for building neural network models.

**Scikit-learn:**

scikit-learn is a machine learning library in Python that provides simple andefficient tools for **d**ata analysis and modeling, including tools for datapreprocessing, model evaluation, and hyperparameter tuning.

These libraries, combined with deep learning frameworks and tools, offer a comprehensive set of resources for developing and deploying skin cancer detection models. It's common for developers to use a combination of these libraries based on their preferences and the specific requirements of this project

## 3.3 ARCHITECTURE:

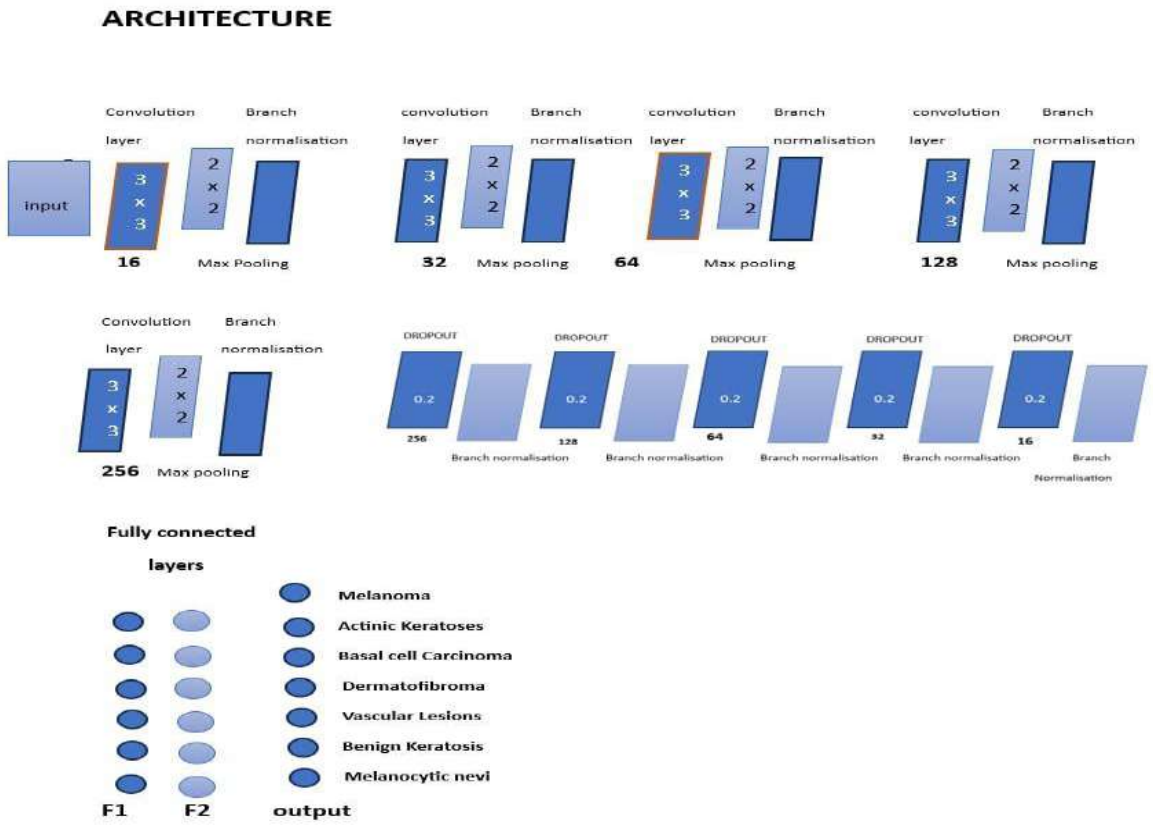



**Fig3.2: Architecture**

Architecture as shown in fig 3.2 we have convolution layers with 3x3, Batch normalization, Max pooling with width of 3x3 and finally we have fully connected layer which can connect responses to predict the type of cancer. Where as in fig 3.4 it is machine generated output while running the CNN Architecture.

Data is collected From fully connected layer then model can classify the cancer types like Melanoma, Actinic Keratoses, Basal Cell Carcinoma, Dermatofibroma, Vascular Lesions, Benign Keratosis and Melanocytic nevi this are the seven type of cancers which are more dangerous if we can't identified early. In Architecture Fig 3.2 we have five types of bit size they are 16, 32, 64, 128 and 256 and then they divided into three layers they are convolution layer with 3x3 kernel size, Max pooling with 3x3 kernel size and finally we have batch normalization after this we dropout layers and batch normalization layers from 256, 128, 64, 32 and 16. We have finally fully connected layers which will connects the data and helps to classify the cancer type with high accuracy.

We have to give an image as input which can give to CNN Architecture which can

helps in classification of skin cancer.

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_10 (Conv2D)          (None, 28, 28, 16)        448

 max_pooling2d_4 (MaxPoolin  (None, 14, 14, 16)        0
 g2D)

 batch_normalization_12 (Ba  (None, 14, 14, 16)        64
 tchNormalization)

 conv2d_11 (Conv2D)          (None, 12, 12, 32)        4640

 conv2d_12 (Conv2D)          (None, 10, 10, 64)        18496

 max_pooling2d_5 (MaxPoolin  (None, 5, 5, 64)          0
 g2D)

 batch_normalization_13 (Ba  (None, 5, 5, 64)          256
 tchNormalization)

 conv2d_13 (Conv2D)          (None, 3, 3, 128)         73856

 conv2d_14 (Conv2D)          (None, 1, 1, 256)         295168

 flatten_2 (Flatten)         (None, 256)               0

 dropout_6 (Dropout)         (None, 256)               0

 dense_10 (Dense)            (None, 256)               65792

 batch_normalization_14 (Ba  (None, 256)               1024
 tchNormalization)

 dropout_7 (Dropout)         (None, 256)               0

 dense_11 (Dense)            (None, 128)               32896

 batch_normalization_15 (Ba  (None, 128)               512
 tchNormalization)

 dense_12 (Dense)            (None, 64)                8256

 batch_normalization_16 (Ba  (None, 64)                256
 tchNormalization)

 dropout_8 (Dropout)         (None, 64)                0

 dense_13 (Dense)            (None, 32)                2080

 batch_normalization_17 (Ba  (None, 32)                128
 tchNormalization)

 dense_14 (Dense)            (None, 7)                 231

=================================================================
Total params: 504103 (1.92 MB)
Trainable params: 502983 (1.92 MB)
Non-trainable params: 1120 (4.38 KB)
_________________________________________________________________
```

**Fig 3.3:** Output of CNN Architectre

# CHAPTER 4

# SOFTWARE REQUIREMENTS

To achieve the mentioned objectives for improving the accuracy adaptability, early detection, reduced false positives/negatives, robustness, real-time classification, integration, interpretability, scalability, and generalization in a Convolutional Neural Network (CNN)-based skin lesion classification system, the following software requirements are crucial:

## 4.1 Deep Learning Framework:

TensorFlow is an open-source machine learning framework crafted by the Google Brain team. It serves as a tool to simplify the creation and deployment of machine learning models, with a particular emphasis on deep learning. With its broad applicability, TensorFlow finds application in diverse domains such as image and speech recognition, natural language processing, and reinforcement learning.

## 4.2 Neural Network Model Design:

Keras, serving as a high-level neural networks API, offers a streamlined platform for constructing and training models. It commonly integrates with TensorFlow as its backend, enhancing its functionality and versatility.

## 4.3 Variable Nonlinear Activation Functions:

Custom Activation Functions or TensorFlow/ PyTorch Extensions: Depending on the framework, you may need to implement or use extensions to incorporate variable nonlinear activation functions. These could include adaptive activation functions like Parametric Rectified Linear Unit (PReLU) or Exponential Linear Unit (ELU).

**Non-linear Activation Function:**

A nonlinear neural network employs transformations that are nonlinear within its layers, incorporating elements like activation functions, convolution, or pooling. Activation functions, integral to this process, facilitate the introduction of nonlinearity within the network that adds nonlinearity to the output of a neuron, such as a sigmoid, tanh, or relu function.

**Purpose of Non-Linear activation functions:**

Nonlinear functions serve as the predominant choice for activation functions due to their effectiveness in enabling neural network models to adjust to diverse datasets and discern

between different outcomes. This adaptability facilitates backpropagation by establishing a relationship between the derivative function and the input, enabling a deeper understanding of how adjustments to input neuron weights can enhance predictions.

**1.Relu:**

The ReLU (Rectified Linear Unit) activation function serves to introduce nonlinearity within neural networks, addressing the issue of vanishing gradients during model training and enabling the extraction of more intricate data relationships. Widely utilized in Convolutional Neural Networks (CNNs), ReLU returns 0 for negative inputs and the input value itself for positive inputs, defined as **f(x) = max(0, x).** Particularly effective in hidden layers, ReLU transforms linear input combinations into nonlinear outputs, enhancing the network's capacity to capture complex data relationships. However, in the output layer, we need to ensure that the predicted values are in a specific range.

**2.Leaky ReLu:**

The Leaky Rectified Linear Unit, or Leaky ReLU, is a variant of the ReLU activation function, featuring a small slope for negative values rather than a flat slope. Unlike ReLU, the slope coefficient in Leaky ReLU is predetermined before training and remains constant throughout training. This activation function addresses the "Dead Neuron" issue in neural networks by permitting a slight negative slope for negative input values. Leaky ReLU finds application in convolutional neural networks, particularly in tasks such as handwritten character recognition, where it aids in filtering extracted features. Serving as an extension of ReLU, Leaky ReLU helps mitigate the "dying ReLU" problem by ensuring that neurons do not become permanently inactive during training.

**f(x) = max(ax, x)**

where: a is small constant typically set value like 0.01

x is the input to the neuron

**3.Parametric Relu:**

Parametric methods in statistics serve the purpose of making assumptions about the distribution shape and parameters in the underlying population. For instance, they may assume a normal distribution and specific parameters such as means and standard deviations.

Parametric ReLU (PReLU) is an evolved version of traditional ReLU and Leaky ReLU activation functions, aiming to refine neural network performance further. PReLU enhances

Leaky ReLU by introducing a learnable parameter for the slope, thereby improving model accuracy and convergence. Importantly, using PReLU doesn't overly burden the neural network's learning process as the additional parameters to learn are equal to the number of channels, which is relatively small compared to the total number of weights the model needs to learn.

**f(x) = ax for x<0**

**x for x>=0**

It does not have zero slope parts it speeds up training

Where: a is small constant typically set value like 0.01

x is the input to the neuron

**4. hyperbolic tangent:**

Hyperbolic tangent (TanH) is a non linear activation function with its center at zero and its value ranging between -1 to 1, A mathematical function commonly used in artificial neural networks for their hidden layers

**F(x)=tanh(x)=(2/1+e-2x)-1**

**5. ELU:**

The Exponential Linear Unit (ELU) is an activation function commonly used in neural networks. It's designed to capture both the benefits of Rectified Linear Units (ReLU) and smooth activation functions like the hyperbolic tangent (tanh).

For values of x greater than zero, elu returns x unchanged.

For values of x less than or equal to zero, it applies the ELU formula using the exponential function and the α parameter to produce the output.

**OPTIMIZER:**

**SoftMax:**

SoftMax function, also referred to as softargmax or normalized exponential function, transforms a vector of k real numbers into a probability distribution encompassing K potential outcomes. It achieves this by exponentiating each output and subsequently normalizing each value by the sum of all exponentials, ensuring that the resultant vector represents probabilities and sums up to one.

$$\textbf{SoftMax (Zj)} = \frac{e^{Z_j}}{\sum_{k=1}^{K} e^{Z_K}} \qquad \text{for j=1,2,…., k}$$

## 4.4 Image Processing Libraries:

OpenCV: Essential for preprocessing dermoscopic images, OpenCV provides tools for image manipulation, filtering, and feature extraction.

## 4.5 Data Management:

Pandas: A Python library for data manipulation that is useful for handling datasets and organizing input data for training.

## 4.6 Model Evaluation:

Scikit-learn: Use Scikit-learn for model evaluation, including metrics like precision, recall, and accuracy.

## 4.7 Development Environment:

Jupyter Notebooks: Use Jupyter Notebooks for interactive development, experimentation, and documentation.

## 4.8 Version Control:

Git: Employ Git for version control, collaboration, and tracking changes in your codebase.

## 4.9 Visualization Tools:

Matplotlib or Seaborn: These libraries help visualize model performance, training curves, and other relevant metrics.

## 4.10 Documentation and Collaboration:

GitHub or GitLab: Use a version control repository platform for collaborative development, code sharing, and documentation.

Ensure compatibility and stability across these software components, and consider creating a virtual environment to manage dependencies. Additionally, adhere to best practices for code organization and documentation to facilitate collaboration and future maintenance.

# CHAPTER 5

# RESULTS AND ANALYSIS

## 5.1 OBSERVATIONS AND ANALYSIS (WITH BALANCED AND UNBALANCED):

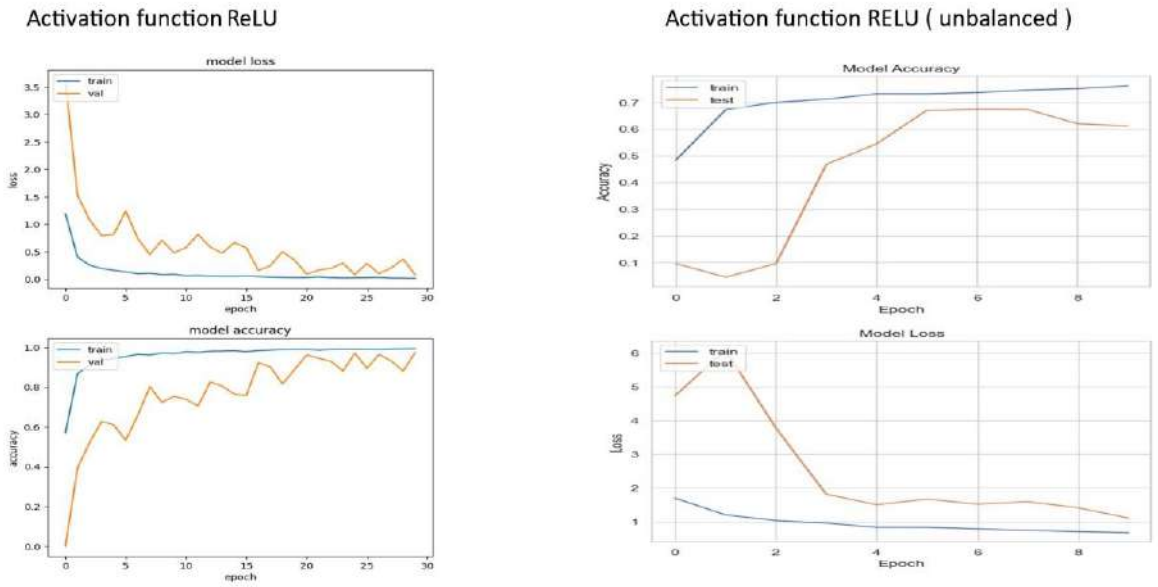



**Fig 5.1**: Activation Function ReLU

Rectified Linear Unit (ReLU) is one of the Non-linear Activation Functions. The above Fig 5.1 represents the Rectified Linear Unit (ReLU) outputs when we train the model with balanced HAM10000 dataset and without balanced or original dataset. From fig 5.1 left side we have trained the model with balanced HAM10000 with 30 epochs for both model loss and model accuracy as shown in Fig 5.1. Above figure right graphs represents the outputs of original HAM10000 dataset with 20 epochs as shown in fig 5.1. The blue line represents the train data and orange line represents the validation data as shown in above figure. In case of balanced dataset we get better results as compared to unbalanced. We got 97.35% model accuracy, 2.07% model loss in case of ReLU activation function.

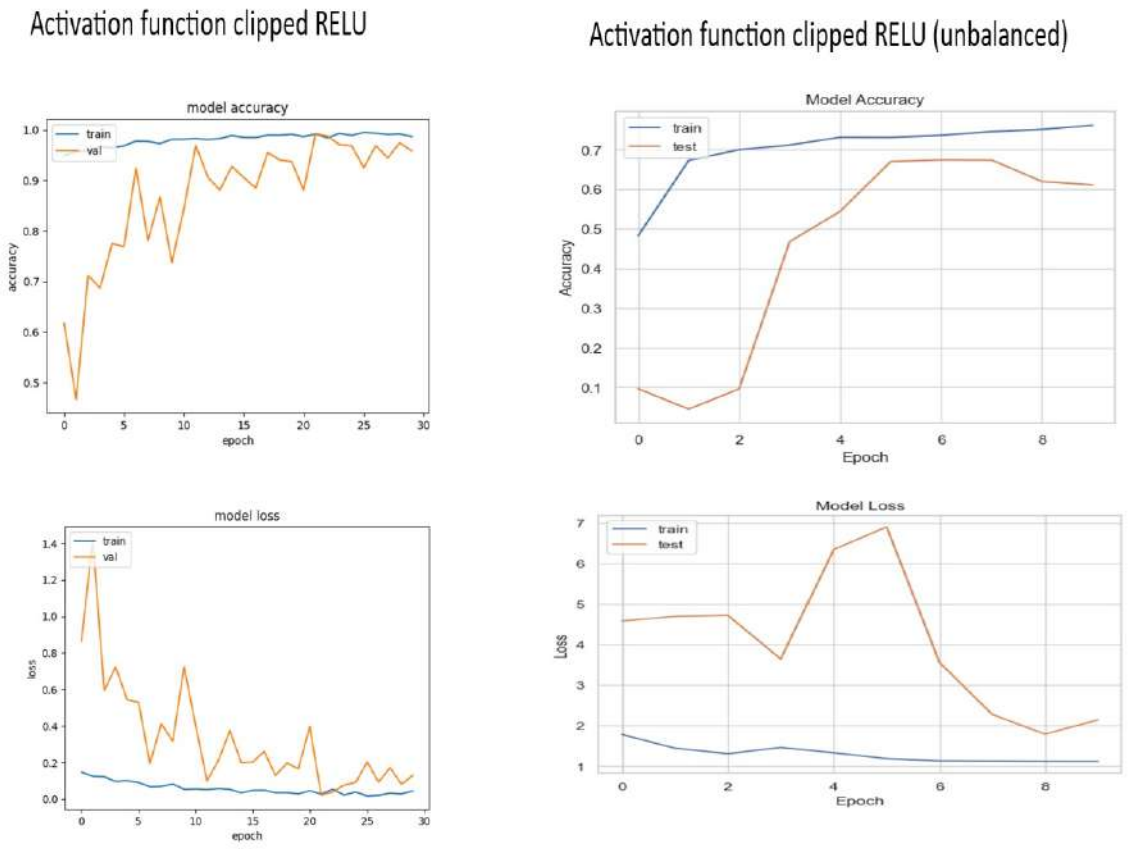



**Fig 5.2:** activation Function Clipped ReLU

Clipped ReLU (CReLU) is one of the Non-linear Activation Functions. The above Fig 5.2 represents the Clipped ReLU (CReLU) outputs when we train the model with balanced HAM10000 dataset and without balanced or original dataset. From fig 5.2 left side we have trained the model with balanced HAM10000 with 30 epochs for both model loss and model accuracy as shown in Fig 5.2. Above figure right graphs represent the outputs of original HAM10000 dataset with 20 epochs as shown in fig 5.2. The blue line represents the train data and orange line represents the validation data as shown in above figure. In case of balanced dataset we get better results as compared to unbalanced. We got 96.69% model accuracy, 4.29% model loss in case of CReLU activation function.

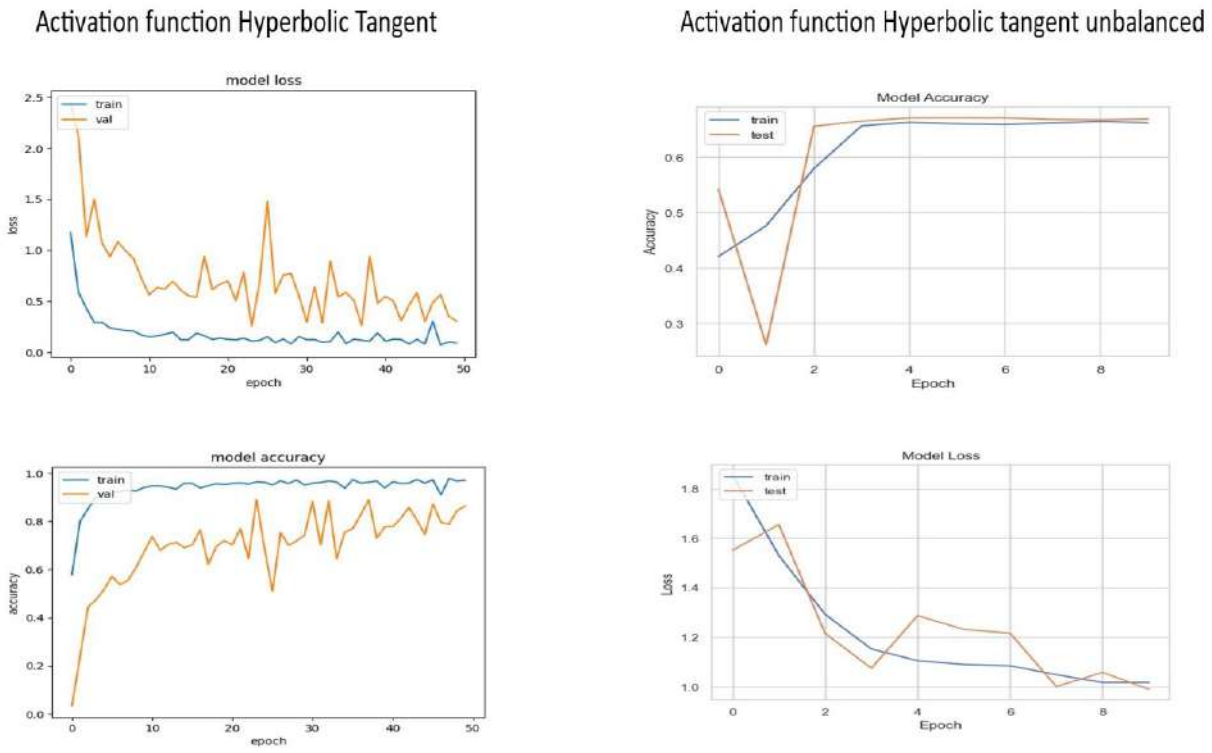



**Fig 5.3:** Activation Function Hyperbolic Tangent

Hyperbolic Tangent(TanH) is one of the Non-linear Activation Functions. The above Fig 5.3 represents the Hyperbolic Tangent (TanH) outputs when we train the model with balanced HAM10000 dataset and without balanced or original dataset. From fig 5.3 left side we have trained the model with balanced HAM10000 with 30 epochs for both model loss and model accuracy as shown in Fig 5.3. Above figure right graphs represent the outputs of the original HAM10000 dataset with 20 epochs as shown in fig 5.3. The blue line represents the train data and the orange line represents the validation data as shown in the above figure. In the case of a balanced dataset we get better results as compared to unbalanced. We got 95.06% model accuracy, 9.01% model loss in case of TanH activation function.

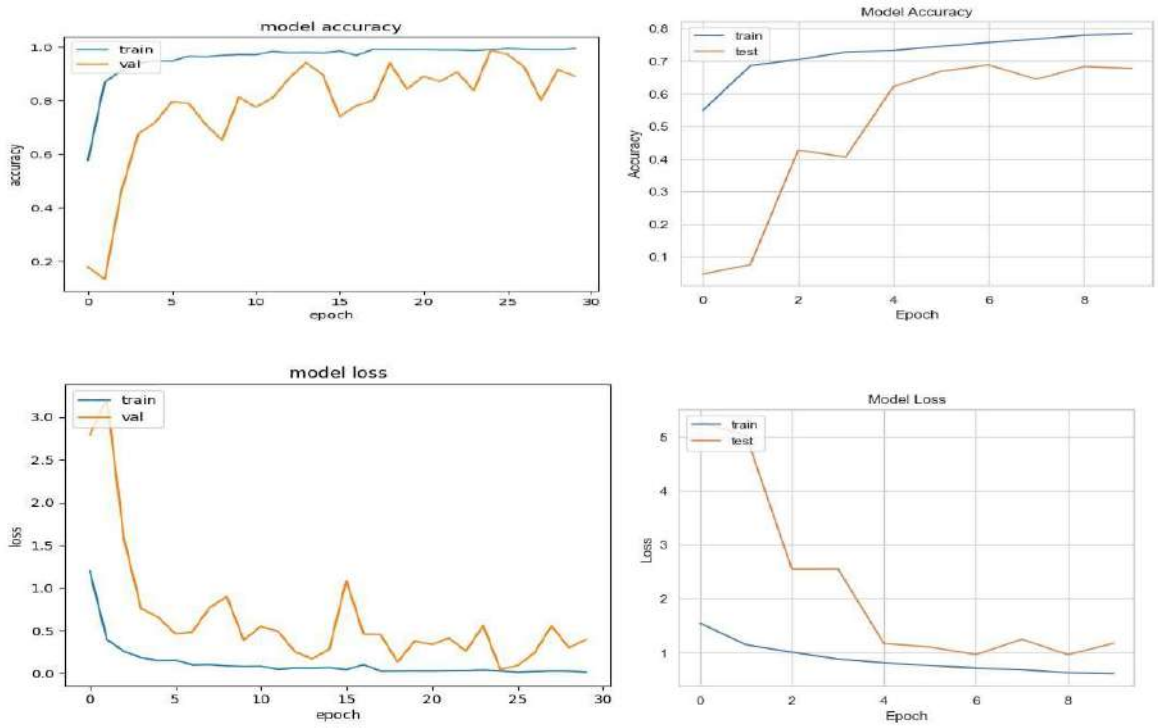



**Fig 5.4:** activation function (PreLE) with balanced and unbalanced dataset

Parametric Rectified Linear Unit (PReLU) is one of the Non-linear Activation Functions. The above Fig 5.4 represents the Parametric Rectified Linear Unit (PReLU) outputs when we train the model with balanced HAM10000 dataset and without balanced or original dataset. From fig 5.4 left side we have trained the model with balanced HAM10000 with 30 epochs for both model loss and model accuracy as shown in Fig 5.4. Above figure right graphs represent the outputs of the original HAM10000 dataset with 20 epochs as shown in fig 5.4. The blue line represents the train data and the orange line represents the validation data as shown in above figure. In the case of a balanced dataset we get better results as compared to unbalanced. We got 95.89% model accuracy, 10.29% model loss in case of PReLU activation function.

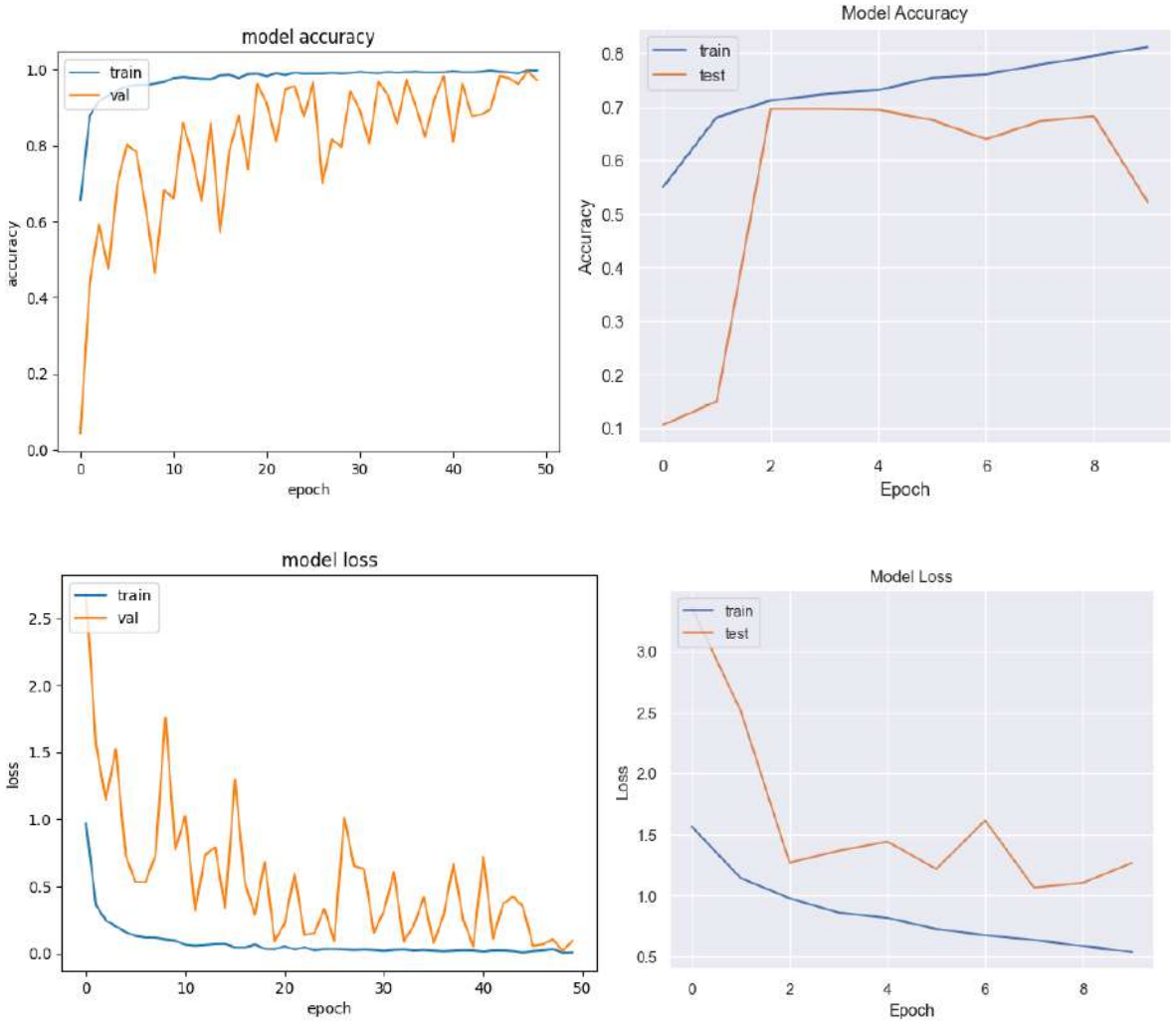



**Fig 5.5:** Leaky ReLU (LReLU) with balanced and unbalanced dataset

Leaky ReLU (LReLU) is one of the Non-linear Activation Functions. The above Fig 5.5 represents the Leaky ReLU (LReLU) outputs when we train the model with balanced HAM10000 dataset and without balanced or original dataset. From fig 5.5 left side we have trained the model with balanced HAM10000 with 30 epochs for both model loss and model accuracy as shown in Fig 5.5. Above figure right graphs represent the outputs of the original HAM10000 dataset with 20 epochs as shown in fig 5.5. The blue line represents the train data and the orange line represents the validation data as shown in above figure. In the case of a balanced dataset we get better results as compared to unbalanced. We got 98.2% model accuracy, 2.5% model loss in case of LReLU activation function.

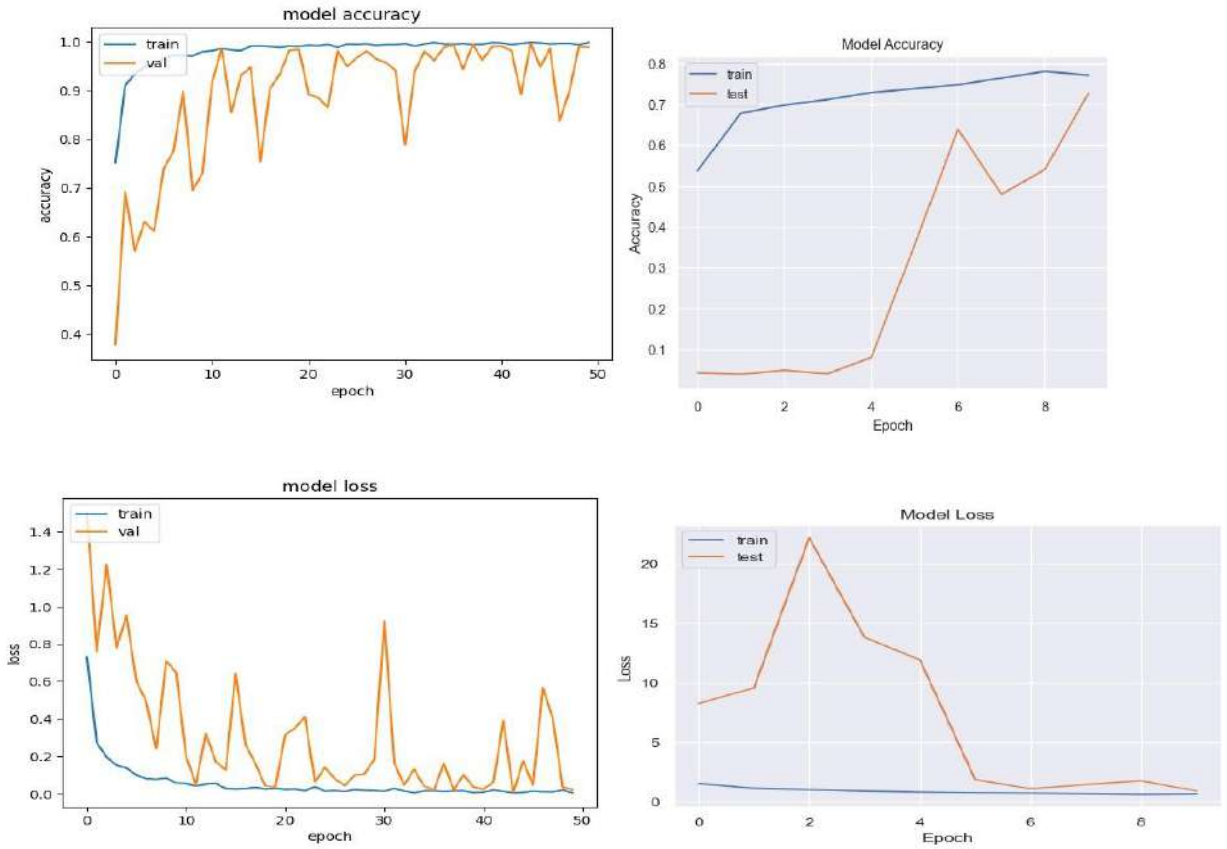



**Fig 5.6:** Exponential Linear Unit (ELU) with balanced and unbalanced dataset

Exponential Linear Unit (ELU) is one of the Non-linear Activation Functions. The above Fig 5.6 represents the Exponential Linear Unit (ELU) output when we train the model with a balanced HAM10000 dataset and without balanced or original dataset. From fig 5.6 left side we have trained the model with balanced HAM10000 with 30 epochs for both model loss and model accuracy as shown in Fig 5.6. Above figure right graphs represent the outputs of the original HAM10000 dataset with 20 epochs as shown in fig 5.6. The blue line represents the train data and the orange line represents the validation data as shown in above figure. In the case of a balanced dataset we get better results as compared to unbalanced. We got 97.5% model accuracy, 1.2% model loss in case of ELU activation function.

## 5.2 CONFUSION MATRIX:


**Fig 5.7**: confusion matrix of activation matrix of ReLU

## 5.3 CALCULATING ACCURACY AND PRECISION THROUGH CONFUSION MATRIX:

Where accuracy refers to how close a measurement is to the true or accepted value. Precision refers to how close measurements of the same item are to each other

ACCURACY:

Accuracy is a measure of how correct a measurement or result is compared to the true value or standard. It's widely used in many fields, including science, math, and statistics. In machine learning and data analysis, accuracy typically indicates the percentage of correctly classified instances in a dataset. However, it's essential to consider other evaluation metrics, particularly in situations with imbalanced data or when different types of errors have differing impacts, as accuracy alone may not provide a complete picture of model performance.

PRECISION:

Precision is a key metric utilized in binary classification tasks within machine learning and statistical analysis. It evaluates the ratio of true positive predictions to all positive predictions made by a model. Essentially, precision gauges the accuracy of positive predictions by assessing how many of the instances flagged as positive are genuinely positive. A high precision score signifies that when the model predicts a positive outcome, it's highly probable to be accurate. Nonetheless, precision singularly might not offer a comprehensive understanding of a model's performance, particularly in scenarios with imbalanced class distributions in the dataset. Therefore, it's often juxtaposed with recall, which quantifies the ratio of true positives among all actual positive instances, to provide a holistic assessment of a classification model's effectiveness.

**Precision = TP/(TP+FP)**

**Accuracy = (TP+TN)/(TP+TN+FP+FN)**

Where : TP = True Positive

FN = False Negative

TN = True Negative

FP = False Positive

## 5.4 Tables:

**Table 5.8:** activation functions results with balanced classes and unbalance classes

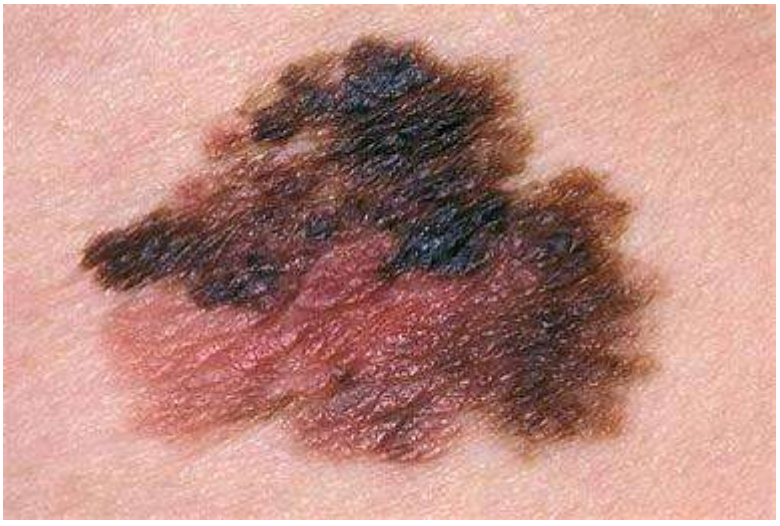
| activation | Model accuracy | Model loss | Val-accuracy | Val-loss |
|---|---|---|---|---|
| **ReLU** | 97.35 | 2.07 | 96.62 | 6.87 |
| **Clipped ReLU** | 96.69 | 4.29 | 95.84 | 12.9 |
| **Hyperbolic tangent** | 95.06 | 9.1 | 86.27 | 3.0 |
| **Leaky ReLU** | 98.2 | 2.5 | 98.0 | 1.8 |
| **ELU** | 97.5 | 1.2 | 97.0 | 2.6 |

**Table 5.9:** activation function with respective values of unbalanced dataset

| Activation functions | Model accuracy | Model loss | Val-accuracy | Val-loss |
|---|---|---|---|---|
| **ReLU** | 76.16 | 67.48 | 61.10 | 99.79 |
| **Clipped ReLU** | 66.60 | 71.83 | 43.90 | 98.19 |
| **Hyperbolic tangent** | 66.20 | 91.71 | 66.88 | 99.03 |
| **Leaky ReLU** | 79.24 | 57.43 | 69.39 | 93.05 |
| **ELU** | 78.42 | 61.11 | 67.75 | 71.11 |

All the above Nonlinear activation functions like (Relu, PReLU, LReLU, CReLU, ELU and TanH) we created a table with model accuracy, model loss, val-accuracy and val-loss as shown in the table 5.8 and 5.9

## 5.5 CANCER DETECTION:



```
1/1 [==============================] - 0s 47ms/step
[2.5030776e-04 5.3434336e-04 1.8283381e-03 6.9733269e-06 4.4555660e-02
 2.9815466e-04 9.5252615e-01]
('mel', 'melanoma')
```

**Fig 5.9:** cancer detection

# CHAPTER 6

# CONCLUSION AND FUTURE SCOPE

## 6.1 CONCLUSION

The exploration of convolutional neural networks (CNNs) for skin lesion classification with variable non-linear activation functions holds significant promise and potential for advancing medical imaging and dermatology. The integration of diverse activation functions into the CNN architecture allows for a more nuanced approach to capturing intricate patterns within skin lesions. The utilization of variable non-linear activation functions provides the CNN with increased flexibility to adapt to the complex and diverse features present in skin lesions. This adaptability is crucial for improving the model's ability to discriminate between different types of lesions. The investigation of different activation functions enables the identification of those that optimize model performance, leading to improved accuracy and generalization. This optimization is essential for reliable and robust skin lesion classification, especially when dealing with variations in image characteristics. Efforts to optimize models for real-time applications and integrate them into clinical workflows are crucial for translating research findings into practical, real-world solutions. Making these models accessible to dermatologists and healthcare professionals can significantly impact diagnostic processes and patient care.

From my model i have observed that balanced dataset can give higher accuracy than unbalanced and also among Nonlinear activation function Leaky ReLu is the best activation function in skin lesion classificatio

## 6.2 FUTURE SCOPE:

As technology continues to advance, The future scope of convolutional neural networks (CNNs) for skin lesion classification with variable non-linear activation functions holds significant potential in the field of medical image analysis and healthcare. The use of variable non-linear activation functions may contribute to improved accuracy in skin lesion classification. Different lesions may exhibit varying levels of complexity, and tailoring activation functions to specific regions of the input space could enhance the model's ability to generalize. Collaboration between machine learning researchers and dermatologists is crucial for the success of skin lesion classification models. Understanding the specific requirements and challenges faced by dermatologists can lead to the development of more clinically relevant models. CNNs for skin lesion classification with variable non-linear activation functions involves a combination of technical advancements, collaboration with healthcare professionals,

and a strong emphasis on ethical considerations to ensure successful and responsible integration into clinical practice. Combine predictions from multiple CNN models with different activation functions or architectures to create ensemble models. Ensemble approaches often lead to improved performance and robustness.

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