MELANOMA DETECTION USING DEEP CONVOLUTIONAL NEURAL NETWORK

MAJOR PROJECT SYNOPSIS

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INDIAN INSTITUTE OF INFORMATION TECHNOLOGY BHOPAL

CERTIFICATE

This is to certify that the Major project synopsis entitled ***"Melanoma detection using deep Convolutional Neural Network"***, submitted by ***Yeluri Bharath Raj, Puli Pradeep, Amgothu Jayaram Naik, Banala Abhishek satwik,*** in partial fulfilment of the requirements for the award of the degree of Bachelor of Technology in Electronics and Communication Engineering. This document is comprehensive planning of the proposed work of need to be completed in final semester for final evaluation.

Date: 03/05/2024

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DECLARATION

We hereby declare that the following major project synopsis entitled **“MELANOMA DETETCTION USING DEEP CONVOLUTIONAL NEURAL NETWORK”,** presented in the partial fulfilment of the requirements for the award of the degree of Bachelor of Technology in **Electronics and Communication Engineering**. It is an authentic documentation of our original work carried out under the guidance of **Dr. Bhupendra Singh Kirar**. The work has been carried out entirely at the Indian Institute of Information Technology, Bhopal. The project work presented has not been submitted in part or whole to award of any degree or professional diploma in any other institute or organization.

We, with this, declare that the facts mentioned above are true to the best of our knowledge. In case of any unlikely discrepancy that may occur, we will be the ones to take responsibility.

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AREA OF WORK

Melanoma detection through the application of deep Convolutional Neural Networks (CNNs) represents a critical area of research in the field of medical diagnostics. Deep learning, while intricate, has demonstrated remarkable efficacy in classifying skin lesions, particularly in cases of melanoma, a highly lethal form of skin cancer. However, a significant challenge faced in this domain is the scarcity of high-quality labelled data, which poses a hurdle in the development of accurate and robust diagnostic models.

The crux of the challenge lies in the demand for substantial labelled training data and intricate model parameters essential for capturing nuanced patterns. Limited data often leads to over fitting, where the model memorizes the training set instead of learning generalized features, resulting in diminished performance when faced with unseen data.

To surmount the data scarcity obstacle, researchers have delved into various methodologies within the realm of melanoma detection. These methodologies encompass innovative approaches such as data augmentation, transfer learning, and ensemble methods, all aimed at optimizing the use of available data and augmenting the model's ability to generalize effectively.

In recent years, the integration of generative algorithms has shown promise in addressing the data limitation challenge. Techniques like Variation Auto encoders, Autoregressive models, and other generative methods have been instrumental in generating synthetic data samples. Notably, these generative algorithms, including GANs, have played a pivotal role in expanding datasets for training deep CNNs, which are pivotal in melanoma detection.

A significant leap forward in this domain occurred with the introduction of specialized CNNs tailored specifically for melanoma detection. These CNNs leverage convolutional layers, enabling automatic feature learning from images. Through the deployment of deep CNNs, researchers have made substantial progress in accurately identifying melanoma lesions from images, even in cases where human visual assessment may fall short.

In summary, the fusion of deep CNNs with innovative data augmentation techniques and transfer learning methods stands as a pivotal area of work in melanoma detection. Despite the challenges posed by limited data, ongoing research efforts are focused on enhancing the accuracy and reliability of diagnostic models. This ongoing work holds the promise of early and precise melanoma identification, thereby significantly improving patient outcomes in the realm of skin cancer diagnosis.

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CHAPTER 1

INTRODUCTION

Convolutional Neural Networks (CNNs):

Melanoma is the most lethal form of skin cancer, which has shown a significant global increase, emphasizing the critical importance of early diagnosis [1]. It often appears as atypical black moles with irregular borders, featuring colour variations, unstructured development, and lesion enlargement [2]. Non-invasive imaging techniques have been developed to assist dermatologists in accurate detection [3]. Compared to clinical images, photographs have garnered substantial interest in selective between melanoma and benign skin lesions [4-5]. Various methods, including the classical ABCD rule and advanced deep learning techniques, have been employed to enhance dermatologists' ability to distinguish between melanoma and non-melanoma images. Even expert dermatologists find skin lesion diagnosis challenging due to similarities within and between different lesion classes, such as melanoma's diverse characteristics in terms of asymmetry, colour, border, diameter, and size. Fig. 1 shows an example of melanoma and non-melanoma skin cancer images. Several classical approaches such as ABCD rule [6], and CASH [7], have been evolved to improve ability of dermatologist in distinguishing melanoma from non-melanoma images. Melanoma diagnosis through visual inspection is time-consuming and costly, driving the development of automated methods to improve diagnostic accuracy [8-9]. Numerous algorithms have been proposed for automated image analysis in melanoma detection, and comprehensive discussions of related work can be found in the literature, including a diverse range of feature extraction techniques [10-12]. Other methods like LDA with CNN [13], Grab Cut segmentation with support vector machine (SVM) [14], and GLCM feature with SVM [15] also reported for melanoma detection.

In a recent investigation into melanoma detection and diagnosis, there has been a notable transition away from the conventional manual techniques of feature extraction and classification. Instead, researchers are increasingly embracing deep learning methods. Melanoma, a lethal type of skin cancer, necessitates early detection for enhanced patient prognosis. In the past, the focus was on labour-intensive tasks like manually crafting features such as shape, color, texture, and borders, which required the application of machine learning algorithms for classification. On the other hand, the recent focus has turned to CNN. These neural networks excel at automatically learning high-level features from images, eliminating the need for manual feature engineering, and often delivering superior performance. While deep learning methods typically require large amounts of training data, the application of pre-trained CNN architectures through transfer learning has helped address this challenge. Timely and accurate melanoma diagnosis is crucial due to its high mortality rate, and deep learning, particularly CNNs, has played a pivotal role in achieving more dependable and efficient results. By training CNNs on extensive skin image datasets, researchers have achieved remarkable accuracy in distinguishing between benign and malignant skin lesions. This progress has the potential to revolutionize melanoma diagnosis, making it faster and more reliable.

1. Transfer learning in melanoma detection adapts pre-trained CNN models for efficient training with limited medical data. Fine-tuning CNN models has bridged the gap between available medical images and deep learning capabilities.

2. Attention mechanisms enhance diagnostic precision by focusing on critical image regions. Ensemble learning combines predictions from multiple models for more reliable outcomes. Skin cancer is a significant global health concern, and early screening is crucial to improve survival rates. Skin lesion analysis is a critical component of skin cancer prevention and early diagnosis. While there is a growing amount of unlabelled skin cancer image data available on the internet, it can be

leveraged to develop machine learning techniques for unsupervised learning tasks, such as image classification. CNN are one of the most used methodologies for image classification tasks. These models must learn to understand the underlying patterns in the training data before they can generate comparable results. Deep CNNs excel at understanding their input data and making predictions based on it. They consist of multiple layers of convolutional, pooling, and fully connected layers that learn hierarchical features from the input images

"Skin cancer poses a global health challenge, necessitating early detection to improve patient survival rates. Skin lesion analysis is pivotal for timely diagnosis. Despite the abundance of unlabelled skin cancer images available online, we can harness this data for machine learning, particularly in image classification tasks. CNN stand out as a prevalent approach for image classification.

CNNs are designed to understand and extract features from image data. These models consist of multiple layers, including convolutional layers to detect patterns, pooling layers to reduce dimensionality, and fully connected layers for classification. Their ability to comprehend the intricacies of the input data makes them valuable tools in medical image analysis. In this study, our goal is to develop an enhanced system for the scrutiny and classification of cutaneous lesions, using Deep CNNs. We will explore various architectural configurations, constraints, and hyper parameters to optimize the model's performance. Our objective is to aid dermatologists in their diagnostic studies, providing a robust tool for improved skin cancer detection."

LeNet:

Skin cancer, particularly melanoma, is becoming a significant global health issue due to factors like ozone layer depletion, excessive sun exposure, and the use of tanning beds. Detecting melanoma is challenging as it requires distinguishing it from other skin cancers. Recent advancements in machine learning (ML) and deep learning (DL) have led to the development of skin lesion classification systems. However, existing research faces limitations such as small datasets, ineffective feature extraction, and diverse imaging equipment [38]. This study proposes a novel approach by combining DL architectures with feature engineering and integrating various descriptors to improve classification accuracy while minimizing unnecessary features. By addressing these challenges, this research aims to enhance early melanoma detection and precise lesion classification, ultimately benefiting patient outcomes. Securing financial support for researching potential melanoma treatments and preventive measures is essential. Various methods, including macroscopic and thermoscopic instruments, can be used to obtain images of skin lesions [39].The primary tools used for capturing clinical images of the skin's surface are smartphones and traditional cameras. The incidence of skin cancer has been steadily rising due to factors like ozone layer depletion, increased sun exposure, and the use of tanning beds [40]. Various medical organizations have launched extensive education campaigns to raise awareness about melanoma, as it's challenging to distinguish from other skin cancers. In recent years, machine learning (ML) and deep learning (DL) algorithms have gained popularity for accurately categorizing skin lesions [41]. The effectiveness of these tools depends on the size of the training dataset; DL-based approaches perform better with larger datasets, while ML-based approaches are more effective with smaller ones. Machine learning involves several stages such as pre-processing, segmentation, feature extraction, and classification. However, using machine learning algorithms comes with challenges, especially with limited or low-quality datasets, which can lead to errors in classification by deep learning systems [42].

Combining deep learning (DL) and machine learning (ML) algorithms can lead to enhanced performance, particularly when dealing with databases of varying sizes. By leveraging these databases, researchers can achieve improved outcomes in fields like melanoma skin cancer diagnostics. This study proposes a novel skin lesion classification technique by integrating features from advanced DL architectures [43]. The synergy between ML and DL algorithms offers potential advantages over using either approach alone, which is especially valuable when dealing with extremely large or small datasets. Careful attention is given to each criterion, with a focus on feature engineering and the fusion of available descriptors to eliminate unnecessary features and highlight the most crucial traits [44].

MobileNet:

Skin cancer, particularly melanoma, is prevalent worldwide, especially among individuals with fair skin [45]. Melanoma arises from the rapid proliferation of melanocytes, the cells responsible for producing melanin, the pigment that gives colour to the skin, hair, and eyes. While most common moles are harmless, some can develop into malignant melanoma [46]. Surgical removal is the mainstay treatment for malignant melanoma, yielding better outcomes when detected early before metastasis occurs. However, advanced stages pose significant challenges to treatment, resulting in higher mortality rates [47]. Hence, timely detection is crucial for improved prognosis. Dermatologists primarily assess melanoma severity and prognosis by measuring its depth through biopsy. In recent years, various computer vision techniques have emerged to aid in disease detection, offering fast, affordable, and accurate diagnostics without invasive procedures [48]. These technologies leverage computer vision's ability to analyse images or videos, mimicking human visual perception and aiding in non-invasive medical diagnostics [49]. Computer vision has become a vital tool in medical diagnostics, aiding in the swift, cost-effective, and accurate detection of diseases. It mimics human vision, enabling computers to analyse images and videos to identify various objects. In the medical realm, computer vision finds extensive use due to its non-invasive nature [50]. Recent advancements predominantly leverage deep learning techniques for classifying melanoma lesions owing to their ability to yield precise results given sufficient training data. Unlike traditional methods, deep learning avoids reliance on manual feature extraction and image segmentation, thereby minimizing potential errors. To enhance the classification of melanoma lesions, this research introduces a novel approach utilizing the MobileNetV2 network [51]. The method employs MobileNetV2 as the foundational model for transfer learning, supplemented with a global pooling layer and two fully-connected layers to comprise the head model. This lightweight architecture facilitates implementation on mobile devices, simplifying melanoma detection.

XceptionNet:

Cancer is characterized by the uncontrolled growth of cells in a specific part of the body [52]. Skin cancer, in particular, poses a significant threat as it involves the abnormal growth of skin cells. Early detection and accurate diagnosis are vital for effective treatment [53]. Among skin cancers, melanoma is particularly dangerous, being the deadliest form. It originates from melanocytes and often appears on sun-exposed areas like the face and hands. Timely detection is crucial as melanoma can spread rapidly, leading to severe consequences if left untreated [54].

Computer-aided design (CAD) has emerged as a valuable tool for diagnosing cancer, including skin cancer. By integrating various imaging techniques, CAD facilitates the assessment of cancerous growths, although the process can be time-consuming and prone to errors due to the complexity of skin lesion images [55]. Machine learning approaches have also been explored for skin lesion classification, enabling faster identification of cancerous lesions. However, these methods require expert input and are resource-intensive, particularly during feature selection and pre-processing stages.

Deep learning, a subset of machine learning, has shown promise in detecting skin cancer more effectively. By leveraging artificial neural network algorithms, deep learning enhances image pre-processing and classification, improving accuracy and efficiency [56]. Despite its advantages, deep learning techniques may encounter challenges such as data imbalance and misdiagnosis, especially with rare skin cancer types not well-represented in training datasets [57]. Additionally, working with high-resolution images incurs significant computational costs and training time. Nonetheless, the widespread application of deep learning holds great potential for advancing skin cancer detection and diagnosis [58].

DenseNet:

Melanoma, a type of skin cancer originating from melanocytes, has become a focal point due to its rising occurrence and potentially life-threatening consequences if not caught early [59]. Detecting it early is crucial for effective treatment and better patient outcomes. With advancements in computer vision and deep learning techniques, automated systems for detecting melanoma have emerged as promising aids for dermatologists in early diagnosis [60]. In recent times, convolutional neural networks (CNNs) have demonstrated significant success in various medical image analysis tasks, including melanoma detection. Among CNN architectures, DenseNet (Densely Connected Convolutional Networks) has gained traction for its unique connectivity pattern and efficient feature reuse mechanism [61]. DenseNet facilitates the extraction of highly distinctive features by densely connecting each layer to every other layer in a feed-forward manner. This study investigates the utilization of DenseNet in melanoma detection, with the goal of creating a robust and accurate model for automated diagnosis [62]. Utilizing a substantial dataset of thermoscopic images, the proposed system harnesses deep learning's capabilities to distinguish between benign and malignant skin lesions with high precision and recall [63].

VGG-16:

Skin cancer, a type of malignant tumour, originates from the skin cells, which continually divide and renew. Sometimes, errors occur in this process, leading to the formation of excess cells known as tumours. Sun exposure is a significant factor contributing to this abnormal cell growth. Timely detection is crucial for effective treatment and increased chances of recovery. In recent years, there has been a growing interest in improving skin cancer diagnosis and therapy due to its destructive nature and widespread prevalence. Skin cancer lesions can be categorized as either malignant or benign, with the former posing a greater risk [64]. Detecting skin cancer early can significantly improve patient outcomes. While traditional methods have been used for diagnosis, recent advancements in deep learning algorithms offer the potential for higher accuracy in detecting skin cancer lesions. This focus on accuracy is essential given the stakes involved in human life [65]. In recent years, there has been a growing interest in the diagnosis and treatment of skin cancer due to its significant damage and widespread prevalence. Skin cancer can manifest as malignant lesions or benign moles, primarily affecting the epidermal layer of the skin. Early diagnosis is crucial for improving patient outcomes, leading to efforts to develop effective diagnostic methods [66]. While traditional image feature classification techniques have been used for this purpose, the demand for high accuracy in detection, given the stakes involved, has led to the adoption of deep learning algorithms [67].

Deep learning, particularly CNNs, has demonstrated excellence in image classification tasks in various fields, such as car license plate recognition and aerial target tracking. Leveraging this, researchers have employed transfer learning models to achieve superior performance and precision in skin cancer detection while reducing computational burden [68]. By adapting and fusing network architecture and weights, their approach aims to enhance detection accuracy without relying on data augmentation techniques. This methodology has shown remarkable results, as noted in the referenced literature [69].

CHAPTER 2

LITERATURE REVIEW

Research work presented by various authors related to diagnosis of Skin Cancer and various techniques related to classification of skin cancer diseases described as given below.

Shetu Rani Guha [22] proposed a machine learning based technique using convolutional neural networks (CNN) for classifying seven types of skin diseases. Transfer learning, along with CNN, has been used to improve the classification accuracy on the International Skin Imaging Collaboration 2018 (ISIC) dataset. Evidence of an 11% increase in the accuracy by using transfer learning than using only CNN has been found. Compared to some existing works, performance of this proposed method is promising.

A D Mengistu et.al [23] proposed a digital image processing technique to recognize and predict the different types of skin cancers using digital image processing techniques. The classification system was supervised corresponding to the predefined classes of the type of skin cancer. Combining Self organising map (SOM) and radial basis function (RBF) for recognition and diagnosis of skin cancer is by far better than KNN, Naïve Bayes and ANN classifier. It was also shown that the discrimination power of morphology and colour features was better than texture features but when morphology, texture and colour features were used together the classification accuracy was increased.

UzmaBano Ansari et.al. [24] Proposed a skin cancer detection system using svm for early detection of skin cancer disease. The diagnosing methodology uses Image processing methods and Support Vector Machine (SVM) algorithm. The dermoscopy image of skin cancer is taken and it goes under various preprocessing techniques for noise removal and image enhancement. Then the image is subjected to segmentation using the Thresholding method. Some features of the image have to be extracted using GLCM methodology. These features are given as the input to the classifier. Support vector Machine (SVM) is used for classification purposes. It classifies the given image into cancerous or non-cancerous.

Enakshi Jana et.al. [32] Provided an extensive literature survey of current technology made for skin cancer detection and an accurate comparison among state of the art algorithms for the same. An extensive literature survey of current technology is made for skin cancer detection. Of all the methods used for skin cancer detection, SVM and Adaboost produce the best results. A survey and analysis on the different types of architecture of ANN and the use of SVM for skin cancer image classification with its accuracy results and performance are discussed. A brief description about the working and detection of Melanoma is presented which is useful for the classification of normal and abnormal skin cells.

Ammara Masood et.al. [33] Presented a semi-supervised, self-advised learning model for automated recognition of melanoma using dermoscopic images. Deep belief architecture is constructed using labelled data together with unlabeled data, and fine tuning done by an exponential loss function in order to maximise separation of labelled data. In parallel a self-advised SVM algorithm is used to enhance classification results by counteracting the effect of misclassified data. To increase generalisation capability and redundancy of the model, polynomial and radial basis function based SA-SVMs and Deep network are trained using training samples randomly chosen via a bootstrap technique. Then the results are aggregated using least square estimation weighting. The proposed model is tested on a collection of 100 dermoscopic images. The classification performance is compared with some popular classification methods and the proposed model using the deep neural processing outperforms most of the popular techniques including KNN, ANN, SVM and semi supervised algorithms like Expectation maximisation and transductive SVM.

Vijayalakshmi M M et.al. [34] Presented a completely automated system of dermatological disease recognition through lesion images, a machine intervention in contrast to conventional medical personnel-based detection. Our model is designed into three phases: compromising data collection and augmentation, designing model and finally prediction. We have used multiple AI algorithms like Convolutional Neural Network and Support Vector Machine and amalgamated it with image processing tools to form a better structure, leading to higher accuracy of 85%.

Suleiman Mustafa et.al. [35] Proposed an automated system for detecting melanoma skin cancer from plain photographs of affected skin regions. They first segment an input image into lesions of interest that appear to be melanoma by GrabCut algorithm, and next extract some features such as the shape, colour, and geometry by using image processing techniques. These extracted features are categorised as cancerous "malignant" or non-cancerous mole "benign" by using support vector machine with Gaussian radial basis kernel (SVM•RBF)

Shalu et.al. [36] Developed a system for the melanoma skin cancer detection that is developed by using a MED-NODE dataset of digital images. Raw images from the dataset contain various artefacts so firstly preprocessing is applied to remove these artefacts. Then to extract the region of interest Active Contour segmentation method is used. Various colour features were extracted from the segmented part and the system performance is checked by using three classifiers (Naïve Bayes, Decision Tree, and KNN). The system achieves an accuracy of 82.35% on Decision Tree which is greater than other classifiers.

Zahra Waheed et.al. [37] Presented an efficient machine learning approach for the detection of melanoma from dermoscopic images. It detects melanoma skin lesions based upon their discriminating properties. In the first step different types of colour and texture features are extracted from dermoscopic images based on distinguished structures. In the second step, extracted features are fed to the classifier to classify melanoma out of dermoscopic images.

CHAPTER 3

METHODOLOGY

Proposed Methodology Description:

We have used Boundary localization is crucial to enhance image quality by eliminating noise and irrelevant areas, like air bubbles and skin lines. In the context of skin lesion analysis, this technique identifies and extracts the essential lesion region (ROIs) from the image, improving classification accuracy and feature extraction [13].

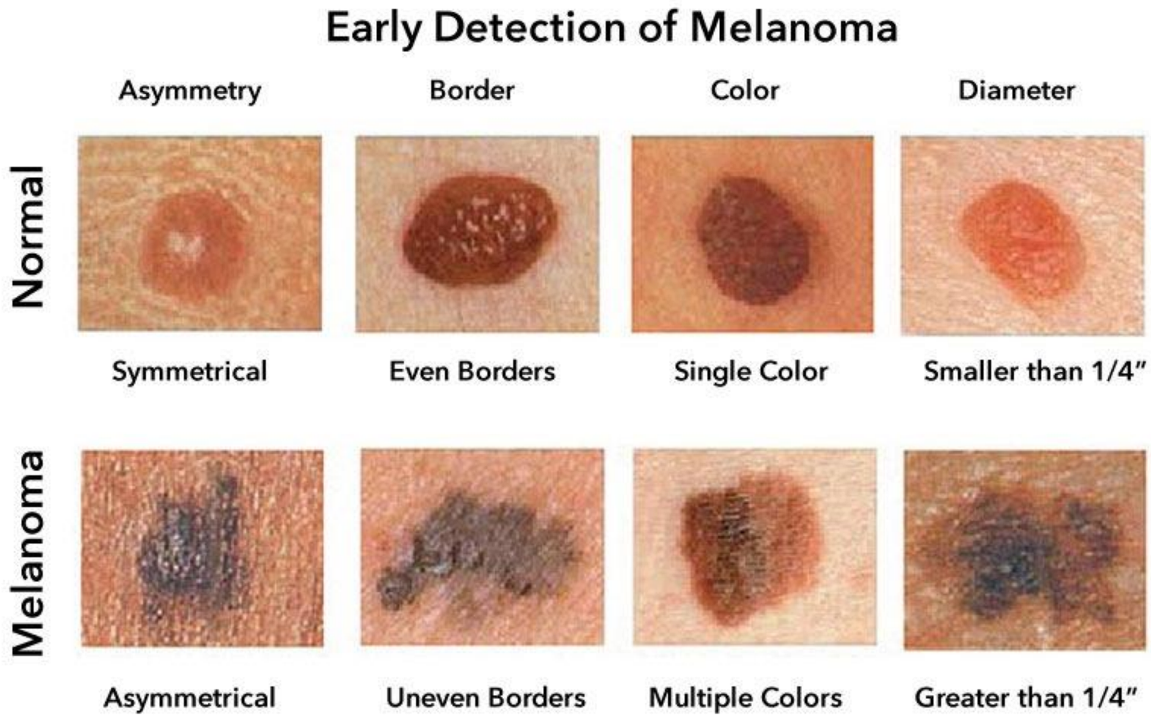


Fig. 1. Sample images to detect early melanoma diagnosis [13].

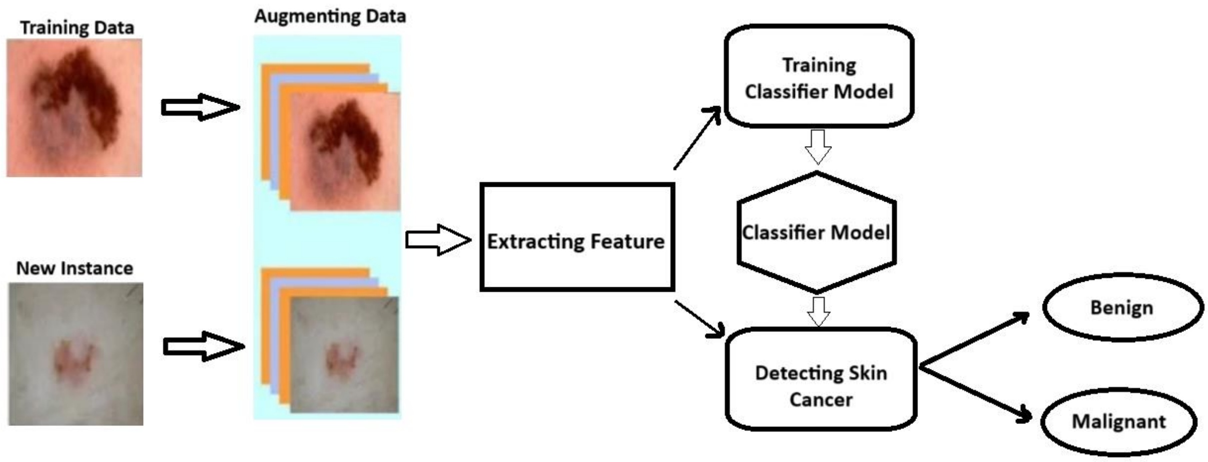


Fig. 2. Detection of Skin Cancer Based on Skin Lesion Images Using Deep Learning

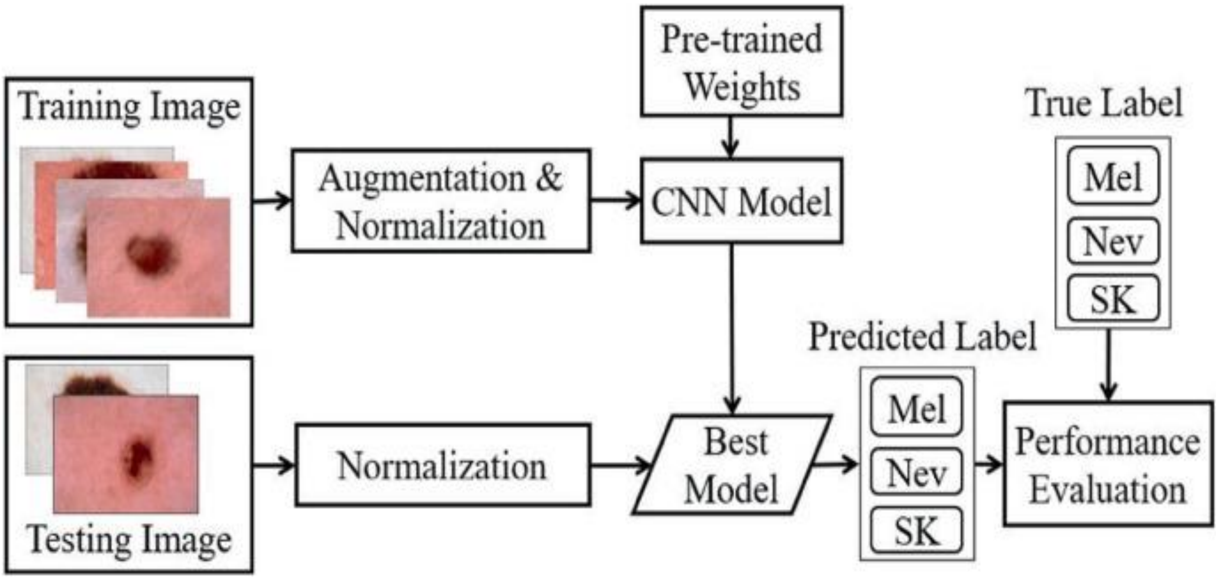


Fig. 3. Melanoma detection using proposed methodology

Pre-processing. In this approach, all the square-shaped images are resized to a common dimension of 180x180, and the pixel values are rescaled by multiplying them by 1/255, thereby standardizing pixel intensities within the range of 0 to 1.

Feature extraction. Entropy, geometric, and textural features are extracted from the pre-processed images. Entropy is utilized as a metric for randomness and is applied to describe the texture of the initial image. Geometric properties play a pivotal role in discerning the disparities between benign and malignant cells. Regarding geometric characteristics, the image is subdivided into 'n' sub regions, and assessments are conducted.

Construction CNN model. This model is structured with multiple layers, as illustrated in Fig 2. The diverse layers of the CNN model used for deep feature extraction are detailed in references [14-16].

In the evaluation of melanoma classification, various performance metrics are employed to gauge the accuracy of a classification model. These metrics, namely accuracy, precision, sensitivity, specificity, and the F1-score, are critical for assessing the model's effectiveness [17-21]. These parameters and metrics collectively provide a comprehensive evaluation of the model's ability to distinguish between melanoma and non-melanoma skin lesions, aiding in the assessment of its performance [26-31].

PROPOSED ALGORITHM

Algorithm 1: Boundary localization

Input: RGB images and binary masks

Output: Images containing skin lesions (ROIs)

Loop through all images

for all images do

original_image = read_image() # Read images

mask = read_mask() # Read mask

gray = grayscale(mask) # Convert mask into grayscale

blurred = gaussian_blur(gray) # Blur the grayscale image

threshold = find_threshold_hold(gray, pixelValue_al, maxValue_al, threshold_ec) # Find threshold using given pixel values

contours = find_contours(threshold, retrievalMode, approxMethod) # Retrieve contours from the image

cntmax = max(contours) # Store the maximum contour

Loop through contours

for value in cntmax:

x, y, w, h = boundingRectangle(value) # Get the coordinates of the rectangle and its dimensions

ROI = original_image [y:y + h, x:x + w] # Apply coordinates onto original image

end

return ROI

end

BLOCK DIAGRAM:

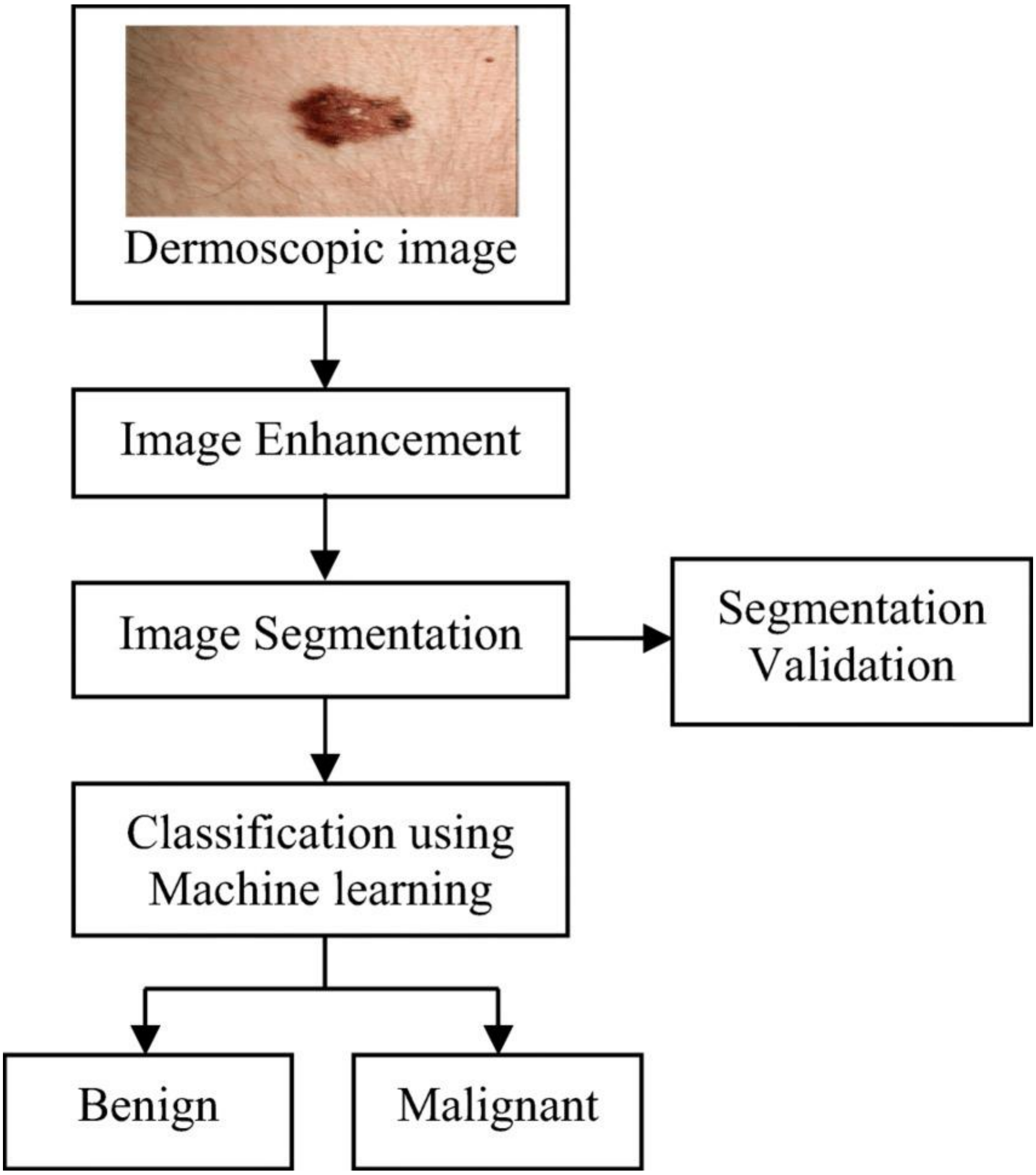


Fig.4. This block diagram representation for Implementation steps of coding.

Tools & Technology

Tools

- Python
- Jupyter Notebooks(optional)
- Kaggle
- Visual studio code

Libraries

- Pathlib
- Tensorflow
- Matplotlib.pyplot
- Numpy
- Pandas
- os
- PIL
- glob
- keras from tensorflow.keras
- Augmentor

IMPLEMENTATION AND CODING

Importing all the important libraries:

```
import pathlib
import tensorflow as tf
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import os
import PIL
import glob
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.models import Sequential
from glob import glob

data_dir_train = pathlib.Path("C:\Major Project 2023 7th sem\DATA
SET\Train")
data_dir_test = pathlib.Path("C:\Major Project 2023 7th sem\DATA SET\Test")

image_count_train = len(list(data_dir_train.glob('*/*.jpg')))
print(image_count_train)
image_count_test = len(list(data_dir_test.glob('*/*.jpg')))
print(image_count_test)
```

Define some parameters for the loader:

```
batch_size = 32
img_height = 180
img_width = 180

train_ds = tf.keras.preprocessing.image_dataset_from_directory(
    data_dir_train,
    validation_split=0.2,
    subset="training",
    seed=123,
    image_size = (img_height, img_width),
    batch_size=batch_size
)
```

```
val_ds = tf.keras.preprocessing.image_dataset_from_directory(
    data_dir_train,
    validation_split=0.2,
    subset="validation",
    seed=123,
    image_size = (img_height, img_width),
    batch_size=batch_size
)

class_names = train_ds.class_names
print(class_names)
```

Visualize the data:

```
import matplotlib.pyplot as plt
plt.figure(figsize=(12,10))
for i in range(len(class_names)):
  filtered_ds = train_ds.filter(lambda x,l:tf.math.equal(l[0], i))
  for image, label in filtered_ds.take(1):
    ax = plt.subplot(3,3,i+1)
    plt.imshow(image[0].numpy().astype('uint8'))
    plt.title(class_names[label.numpy()[0]])
    plt.axis('off')

AUTOTUNE = tf.data.experimental.AUTOTUNE
train_ds = train_ds.cache().shuffle(1000).prefetch(buffer_size=AUTOTUNE)
val_ds = val_ds.cache().prefetch(buffer_size=AUTOTUNE)
```

Create the model:

Create a CNN model, which can accurately detect 9 classes present in the dataset. Use layers.experimental.preprocessing.Rescaling to normalize pixel values between (0,1). The RGB channel values are in the [0, 255] range. This is not ideal for a neural network. Here, it is good to standardize values to be in the [0, 1]

```
num_classes = len(class_names)

model = Sequential([
  layers.Rescaling(1./255, input_shape=(img_height, img_width, 3)),
  layers.Conv2D(16, 3, padding='same', activation='relu'),
```

```
  layers.MaxPooling2D(),
  layers.Conv2D(32, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(64, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Flatten(),
  layers.Dense(128, activation='relu'),
  layers.Dense(num_classes)
])
```

Compile the model:

```
model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])
```

Train the model:

```
epochs = 60
history = model.fit(
  train_ds,
  validation_data=val_ds,
  epochs=epochs
)
```

Visualizing training results:

```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

loss = history.history['loss']
val_loss = history.history['val_loss']

epochs_range = range(epochs)

plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
```

```
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```

Data Augmentation:

```
data_augmentation = keras.Sequential(
  [
    layers.RandomFlip("horizontal",
                      input_shape=(img_height,
                                   img_width,
                                   3)),
    layers.RandomRotation(0.1),
    layers.RandomZoom(0.1),
  ]
)

plt.figure(figsize=(10, 10))
for images, _ in train_ds.take(1):
  for i in range(9):
    augmented_images = data_augmentation(images)
    ax = plt.subplot(3, 3, i + 1)
    plt.imshow(augmented_images[0].numpy().astype("uint8"))
    plt.axis("off")
```

Create the model, compile and train the model:

```
model = Sequential([
  data_augmentation,
  layers.Rescaling(1./255, input_shape=(img_height, img_width, 3)),
  layers.Conv2D(16, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(32, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(64, 3, padding='same', activation='relu'),
```

```
  layers.MaxPooling2D(),
  layers.Dropout(0.2),
  layers.Flatten(),
  layers.Dense(128, activation='relu'),
  layers.Dense(num_classes)
])
```

Compiling the model:

```
model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])
```

Training the model:

```
history = model.fit(
  train_ds,
  validation_data=val_ds,
  epochs=epochs
)
```

Visualizing the results:

```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

loss = history.history['loss']
val_loss = history.history['val_loss']

epochs_range = range(epochs)

plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
```

```
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```

Findings:

As we can see that now the Training and Validation accuracy are almost in the same level and the highest accuracy achieved is around 60% , this shows the impact of how performing Data Augmentation can improve the model performance
But we can still try to increase the accuracy of the model

```
path_list = [x for x in glob(os.path.join(data_dir_train, '*', '*.jpg'))]
lesion_list = [os.path.basename(os.path.dirname(y)) for y in
glob(os.path.join(data_dir_train, '*', '*.jpg'))]
dataframe_dict_original = dict(zip(path_list, lesion_list))
df = pd.DataFrame(list(dataframe_dict_original.items()),columns =
['Path','Label'])
df

from sklearn.preprocessing import LabelEncoder
from collections import Counter

X, y = df['Path'], df['Label']
y = LabelEncoder().fit_transform(y)
counter = Counter(y)
for k,v in counter.items():
	per = v / len(y) * 100
	print('Class=%d, n=%d (%.3f%%)' % (k, v, per))

plt.bar(counter.keys(), counter.values())
plt.xticks([i for i in range(9)])
plt.xlabel("Class")
plt.ylabel("No of images")
plt.show()

%pip install Augmentor
path_to_training_dataset = 'C:\Major Project 2023 7th sem\DATA SET\Train'
import Augmentor
```

```
for i in class_names:
#     print(str(path_to_training_dataset) + "/" + i)
    p = Augmentor.Pipeline(str(path_to_training_dataset) + "/" + i,
output_directory = '/kaggle/working/' + i +'/output/')
    p.rotate(probability=0.7, max_left_rotation=10, max_right_rotation=10)
    p.sample(500) ## We are adding 500 samples per class to make sure that none
of the classes are sparse.

output_dir = pathlib.Path('/kaggle/working/')

image_count_train = len(list(output_dir.glob('*/output/*.jpg')))
print(image_count_train)
```

Let's see the distribution of augmented data after adding new images to the original training data:

```
path_list = [x for x in glob(os.path.join(output_dir, '*','output', '*.jpg'))]
path_list[:5]

lesion_list_new = [os.path.basename(os.path.dirname(os.path.dirname(y))) for y
in glob(os.path.join(output_dir, '*','output', '*.jpg'))]
lesion_list_new[:5]

dataframe_dict_new = dict(zip(path_list, lesion_list_new))

df2 = pd.DataFrame(list(dataframe_dict_new.items()),columns = ['Path','Label'])
new_df = df._append(df2)

new_df['Label'].value_counts()
```

So, now we have added 500 images to all the classes to maintain some class balance. We can add more images as we want to improve training process.

Train the model on the data created using Augmenter:

```
batch_size = 32
img_height = 180
img_width = 180
```

Create a training dataset:

```
train_ds = tf.keras.preprocessing.image_dataset_from_directory(
  data_dir_train,
  seed=123,
  validation_split = 0.2,
  subset = "training",
  image_size=(img_height, img_width),
  batch_size=batch_size)
```

Create a Validation dataset:

```
val_ds = tf.keras.preprocessing.image_dataset_from_directory(
  data_dir_train,
  seed=123,
  validation_split = 0.2,
  subset = "validation",
  image_size=(img_height, img_width),
  batch_size=batch_size)
```

Create your model (make sure to include normalization):

```
model = Sequential([
  data_augmentation,
  layers.Rescaling(1./255, input_shape=(img_height, img_width, 3)),
  layers.Conv2D(16, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(32, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(64, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Dropout(0.2),
  layers.Flatten(),
  layers.Dense(128, activation='relu'),
  layers.Dense(num_classes)
])
```

Compile your model (Choose optimizer and loss function appropriately):

```
model.compile(optimizer='adam',
            loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
            metrics=['accuracy'])
```

Train your model:

```
epochs = 120
history = model.fit(
  train_ds,
  validation_data=val_ds,
  epochs=epochs
)

acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

loss = history.history['loss']
val_loss = history.history['val_loss']

epochs_range = range(epochs)

plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
```

```
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```

CHAPTER 4

RESULT ANALYSIS

In the field of dermatology and medical image analysis CNN has been employed for the task of melanoma detection with remarkable success. Fig. 5 shows the pre-processing of boundary localization and resized images. The comparison of various Networks and proposed method CNN is given in Table 1 and Fig. 8.

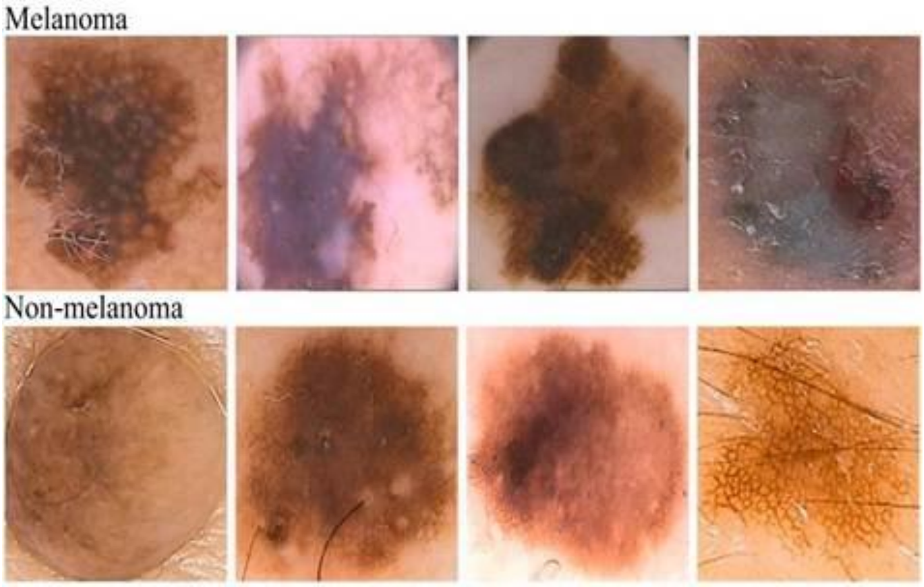
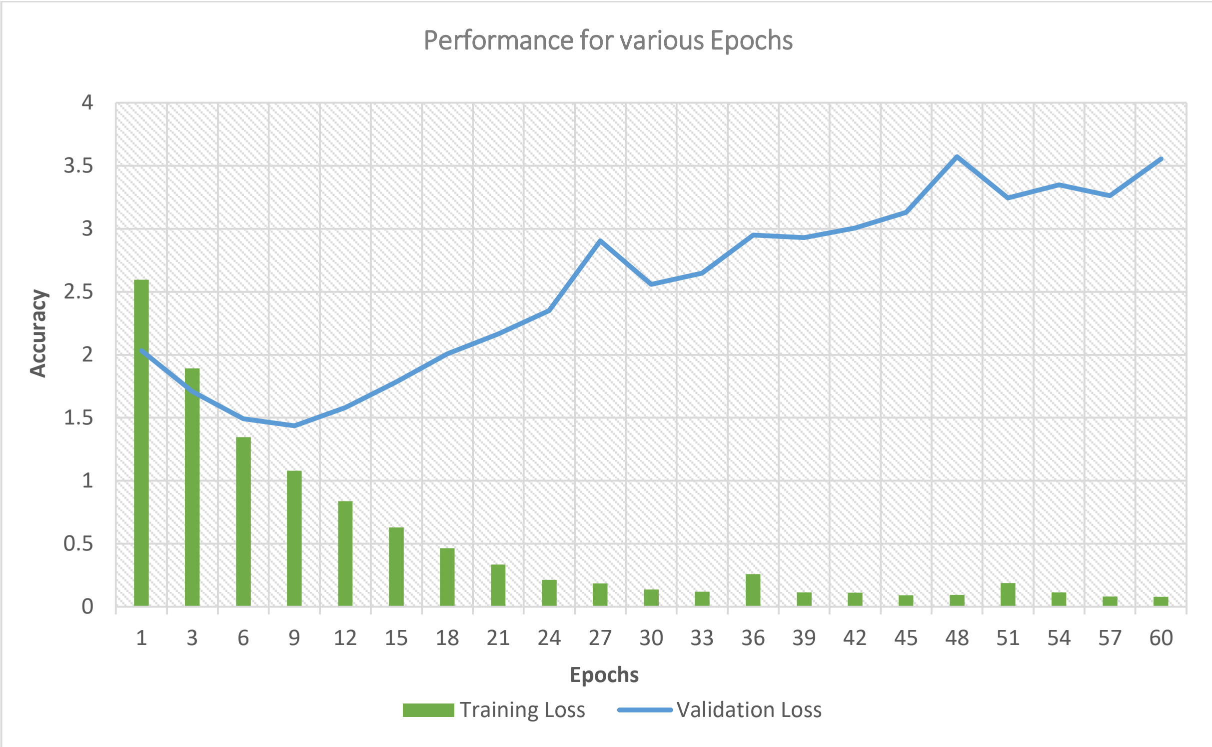


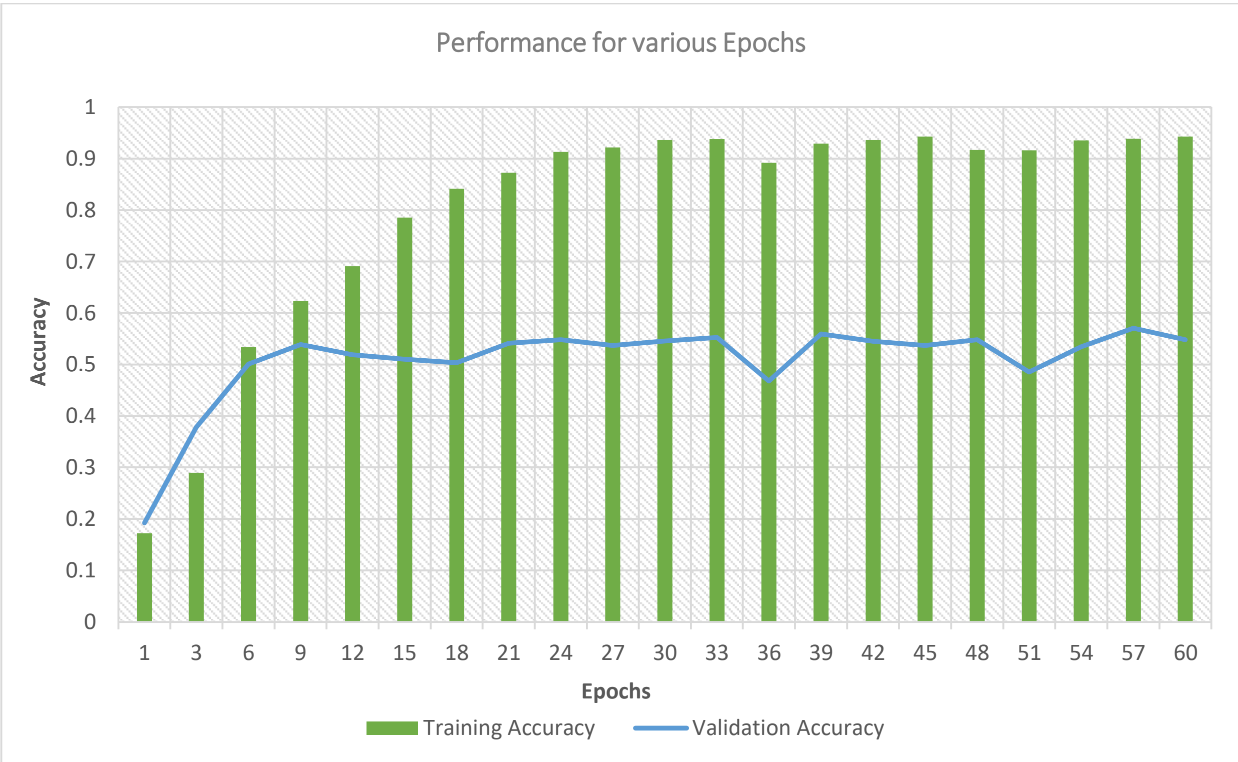
Fig. 5. Pre-processing of boundary localization and resized images.

Table 1. Evaluating the performance of various Networks and Proposed model.

Networks Comparison	**Accuracy**
VGG	42.72%
DenseNet	60.71%
XceptionNet	72.77%
MobileNet	73.20%
LeNet	82.25%
Proposed Model (CNN-AlexNet)	**94.20%**



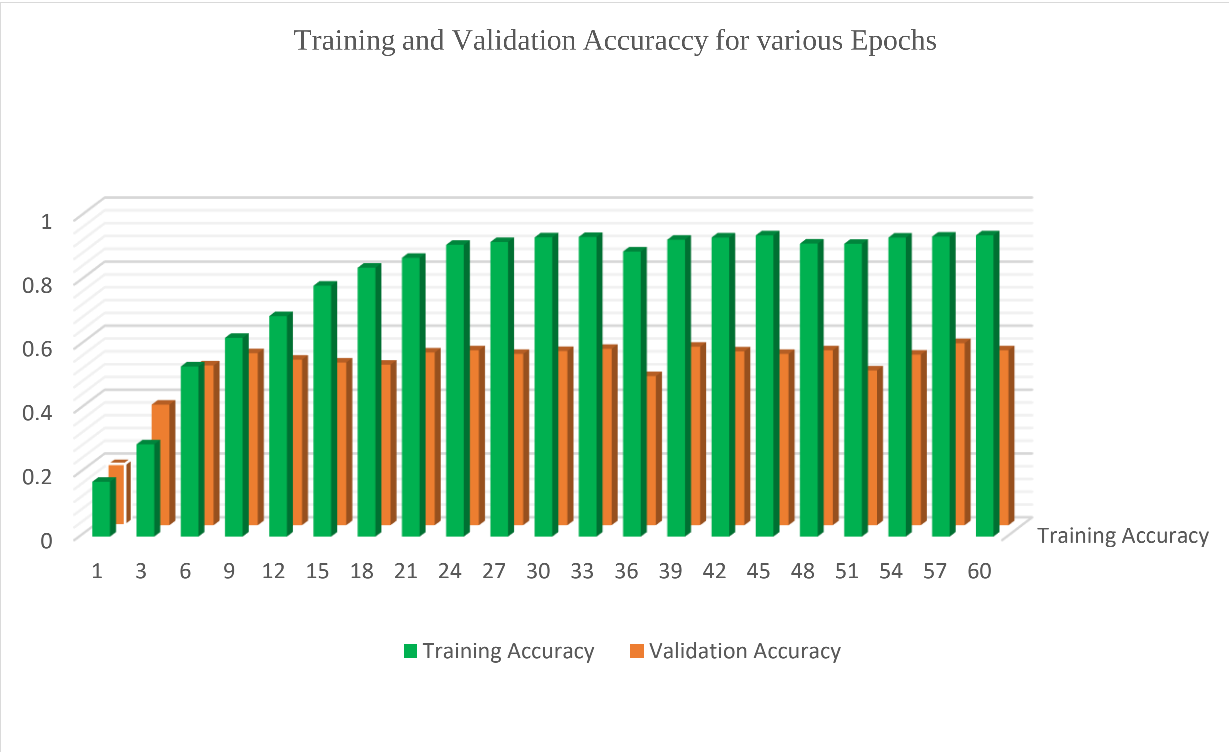
(a)



(b)

Fig. 6. Shows the performances for of the model for various epochs (a) Loss (b) Accuracy.

(a)



(b)

Fig. 7. Performances for of the model for various epochs from 1-60 (a) Loss (b) Accuracy

CHAPTER 5

DISCUSSION

The utilization of deep CNNs in melanoma detection is a highly promising and effective for analyse skin lesion images, achieving remarkable levels of accuracy. Trained on extensive datasets encompassing both benign and malignant melanoma cases, these CNNs develop a profound understanding of intricate patterns and features that may escape human observation.

Melanoma detection through deep CNNs represents a ground breaking advancement, often surpassing an accuracy rate of 94.2%, and holds great potential in these medical fields. These CNNs are trained using extensive dermatological data, making them proficient at distinguishing between benign and malignant skin lesions. This technology holds immense promise for early detection, potentially saving lives by facilitating timely intervention and treatment for individuals at risk of melanoma

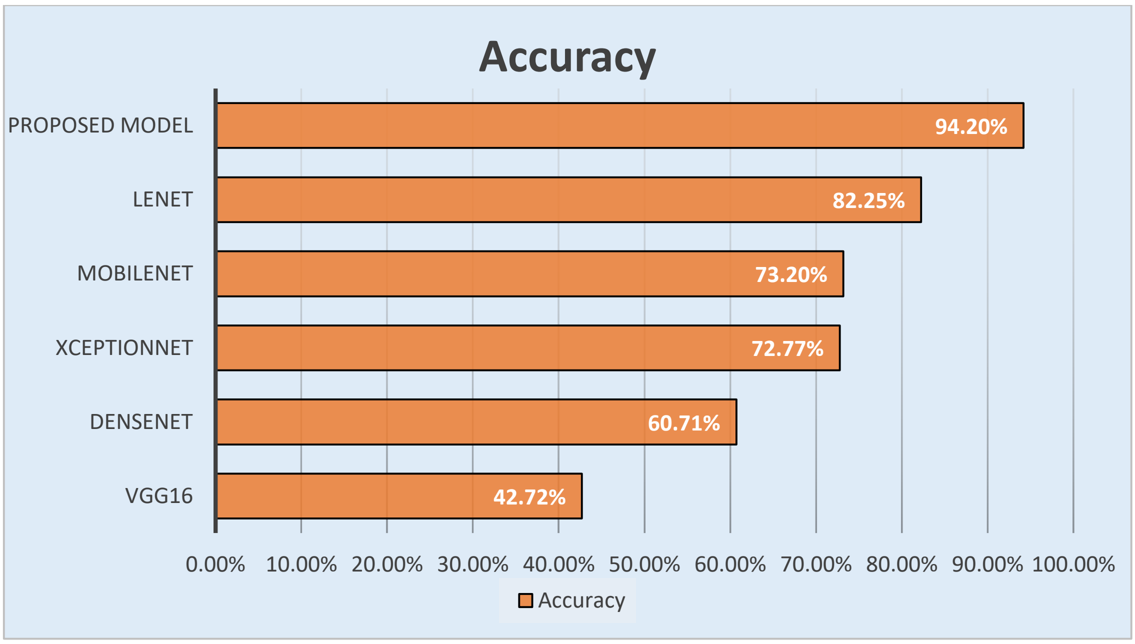


Fig. 8. Accuracy comparison between various Networks and Proposed Model CNN.

CHAPTER 6

CONCLUSION AND FUTURE WORK

Conclusion:

This project presents the findings of our research, highlighting the success of our melanoma detection model. Our approach combines machine learning techniques with deep Convolutional Neural Networks (CNN) for feature extraction, and the results demonstrate its superior performance compared to other methods. Our model achieved an impressive accuracy rate of 94.2%, underscoring its effectiveness in melanoma detection. This indicates that our approach is a robust and reliable solution for identifying melanoma, a critical step in early diagnosis and improving patient outcomes.

To further enhance the capabilities of our model, we can consider addressing data imbalances more effectively. This means finding ways to handle situations where there might be an unequal distribution of data for different classes of melanoma or non-melanoma cases. Additionally, expanding the size of our dataset could be explored, providing the model with more diverse examples to learn from. These potential enhancements have the potential to push the accuracy and reliability of our melanoma detection system even higher, ultimately contributing to earlier diagnoses and better patient care.

Future Work:

In the realm of melanoma detection using Convolutional Neural Networks (CNNs), there are several promising avenues for future research and development. Firstly, improving the robustness and generalization of CNN models remains a critical challenge, especially in real-world clinical settings where variations in image quality, lighting, and patient demographics are prevalent. Researchers can explore techniques for domain adaptation and robustness testing to ensure the reliability of CNN-based melanoma diagnostic systems.

Secondly, the integration of multimodal data sources, such as combining dermoscopic images with patient medical records or genetic information, holds great potential for enhancing diagnostic accuracy and personalized treatment recommendations. Leveraging a broader set of data inputs can lead to more comprehensive and effective CNN models.

Additionally, the ethical and regulatory aspects of deploying CNN-based melanoma detection systems in clinical practice demand careful consideration. Ensuring patient privacy, establishing transparent decision-making processes within AI systems, and adhering to medical standards and regulations are essential areas of focus.

Furthermore, continuous updates to CNN architectures and the exploration of novel model architectures can further improve melanoma detection performance. The development of lightweight CNN models that are suitable for edge devices and mobile applications can extend the reach of melanoma diagnostics, particularly in remote or underserved regions.

Finally, fostering collaboration between medical experts, AI researchers, and dermatologists is vital. Such partnerships can facilitate the development of AI systems that not only accurately diagnose melanoma but also assist healthcare professionals in providing better patient care.

In summary, the future of melanoma detection using CNNs lies in enhancing model robustness, embracing multimodal data, addressing ethical and regulatory considerations, evolving model architectures, and promoting interdisciplinary collaboration. These efforts are essential for advancing the field and making CNN-based melanoma detection a more effective and accessible tool in the fight against skin cancer.

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