



Fusion Based Learning Approach for Melanoma Skin Cancer Detection through Multi-Stage Convolutional Neural Networks

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Abstract

Melanoma is one of the forms of skin cancer that affects people worldwide. Research indicates that nearly 75% of the global population has been impacted by melanoma. Early detection and treatment of melanoma significantly increase survival rates. However, detecting melanoma in its early stages can be challenging because dermatologists typically rely on visual examination and biopsy analysis, which is both time-consuming and labor-intensive. This highlights the need for automated, efficient methods to identify melanoma at earlier stages. Skin cancer is generally classified into two categories: melanoma and benign tumors. The goal of this study is to facilitate the early detection of melanoma by employing deep learning techniques, specifically convolutional neural networks (CNNs), to distinguish between melanoma and benign lesions using the ISIC dataset. The proposed model achieves an accuracy of 80.80%, outperforming previous approaches by offering faster and more accurate melanoma detection.

Keywords: Skin cancer; Melanoma; Convolutional neural networks; Classification; Deep learning Algorithms

1. Introduction

Melanoma has the highest mortality rate among all types of skin cancer. It becomes life threatening when left untreated and spreads beyond the dermis layer of the skin [1]. According to Survey by the World Health Organization (WHO), the number of melanoma (cancerous) cases continues to rise annually. Early detection significantly improves the chances of survival. A biopsy is a common medical procedure used to determine whether sample is cancerous or non-cancerous. Based on the symptoms and characteristics, a dermatologist can assess the stage of infection and determine whether it is in its early stages or has developed into a tumour. If a tumour is confirmed, surgery is usually required, which can be costly, especially for older patients. When skin cancer is detected early, the likelihood of a successful cure can be as high as 92% [2]. With advancements in modern technology, deep learning techniques are increasingly being utilized for the computation and early detection of skin cancer. Automated models are trained to recognize skin cancer based on feature extraction and attribute classification. The datasets are processed to create an interconnected system that aids in decision-making [3]. To develop a sustainable solution, support from the biomedical field is essential for optimizing decision-making processes, which can be quite challenging. This effort is further reinforced by various research communities through approaches like attribute-based classification using machine learning techniques, image processing, Region of Interest (RoI) extraction, and more [4].

Many people believe melanoma is always a dark, raised skin lesion, typically resulting from tumours that develop from pigment cells. However, in some cases, melanoma cells lose their pigment and may appear partially or completely light pink, white, or tan instead of dark [5]. Melanoma symptoms can often be detected using the basic Primary ABCDE method, where A been asymmetry, B for border, C is color, D is diameter, and E is for evolving

along with the presence of "ugly duckling" sign. Timely, efficient, and early diagnosis is very crucial for prompt treatment and improved survival rates. In the raw images obtained for analysis, elements like hair, skin lines, and background noise are often present. Therefore, it is essential to remove these unwanted elements, retaining only the necessary features to ensure the image is suitable for accurate analysis.

Convolutional neural networks, or CNNs, have consistently produced positive results when used to diagnose skin cancer and have shown exceptional performance in identifying picture patterns [7]. Deep Convolutional Neural Networks (DCNNs) are known for their exceptional accuracy in making early predictions, even though there are a number of automated techniques for detecting skin cancer. Because of advancements in research, melanoma can now be diagnosed earlier, increasing the survival rate to 94.1% between 2014 and 2020.

2. Related Work

Nabin K. Mishra et al., [5] proposed an overview of various approaches for melanoma identification using input dermoscopic images by emphasizing the concept of image processing and deep learning techniques in analysis of dermoscopic images and increasing accuracy. It also highlighted the importance of feature extraction, image classification, and its lesion segmentation, highlighting each of these methods that are essential in precise identification of melanoma skin cancer detection.

Thurnhofer-Hemsi, K et al., [6] proposed a novel Deep learning architecture for the diagnosis and identification of skin cancer in this research. The novel method known as Transfer learning was introduced to identify and categorize various types of skin cancer. Data augmentation process was applied to improve the accuracy and performance of the dataset, the dataset used was HAM10000, which is a larger image set consisting of 10000 Dermoscopic Images.

Farea et al. 2024 [7] introduced the concept of Xception Convolutional Neural Network (CNN) and the Artificial Bee Colony (ABC) algorithm. The both methods were combined in his research to create a novel hybrid model. They employed this by optimizing the CNN's starting weights; this combination aids to improve the skin cancer classification accuracy. Along with transfer learning, the study combined the use of CNN models that have been trained. By using this hybrid method, this model enhanced its performance on fresh datasets by utilizing the knowledge already present in previously trained networks.

Arshad A. Hussein et al. [8] proposed the analysis of various machine-learning algorithms, such as Convolutional Neural Networks (CNN), K-Nearest Neighbour (KNN) and Support Vector Machines (SVM). It discussed about various type of Skin cancer like melanoma, squamous cell carcinoma, and basal cell carcinoma, and other forms of skin cancer. It also highlighted each methods unique features and diagnostic difficulties, which are very important for researchers and dermatologist to identify particular type of skin cancer.

Harsh Bhat et al. [9] provided a review of several machine-learning techniques, such as Support Vector Machines (SVM), K-Nearest Neighbours (KNN), and Convolutional Neural Networks (CNN), They also listed the Advantages and Disadvantages of each melanoma detection method. The paper also highlighted the importance of early-stage melanoma detection in raising patient, which improves the survival rates is emphasized by the authors. Additionally, in contrast to conventional machine learning techniques, the significance of deep learning methods like CNNs is emphasized. These leading-edge methods help in the identification and classification of skin cancer while dropping the requirement for preliminary preprocessing.

Melarkode et al., [10] studied both conventional approaches like random forests and neural networks as cutting-edge methods like deep learning and machine learning techniques. It also identifies existing difficulties and possible methods towards better skin cancer diagnosis. The research covered in this study supported the fundamental idea of using deep learning (DL), machine learning (ML), and artificial intelligence (AI) models for the diagnosis of skin cancer.

Nancy et al., 2023 [11] investigated various deep learning (DL) and machine learning (ML) methods for skin cancer diagnosis and classification, which helped to improve diagnostic accuracy. Feature extraction plays an important part of machine learning since it allows the use of domain-specific features to effectively classify skin lesions by making use of their fundamental characteristics.

Prity et al. [12] proposed four different architectures that are incorporated one single model called RvXmBlendNet. By utilizing the advantages of each model, this combination seeks to enhance overall performance in the diagnosis and classification of skin cancer. In order to assist the model, concentrate only on key regions of the images and to improve its capacity to identify subtle patterns, which is a crucial component of medical imaging. The architecture also incorporates adaptive content blocks and classy attention mechanisms.

Shivangi Jain et al. [13] this study presents a computer-aided method for detecting melanoma skin cancer using image processing technologies. The image of the skin lesion is fed into the system, which uses state-of-the-art image processing algorithms to examine it and determine whether skin cancer existed. Using texture, size, and shape analysis for image segmentation and feature phases, the Lesion Image analysis tools check for the different Melanoma parameters, such as Asymmetry, Border, Color, Diameter, (ABCD), etc. The image is classified as either a melanoma cancer lesion or normal skin using the derived feature parameters.

Hiam Alquran et.al [14] Proposed the techniques used in this study include gathering dermoscopy image databases, pre-processing, segmenting using thresholding, statistical feature extraction using Gray Level Co-occurrence Matrix (GLCM), Asymmetry, Border, Color, Diameter (ABCD), etc., feature selection using Principal component analysis (PCA), calculating total Dermoscopy Score, and classification using Support Vector Machine (SVM). The results demonstrate that the achieved classification accuracy is increasing. Non-invasive medical computer vision or medical image processing plays an increasingly important role in clinical diagnosis of various diseases.

3. Data Analysis

A. Dataset

The dataset consisting of 2357 images of Malignant (cancerous) and Benign (non- cancerous), from the International Skin Imaging Collaboration (ISIC) were Employed for this process. All the images collected were arranged according to the classification when obtained from ISIC, and all subsets were obtained into the same number of images. Figure 1 shows the Visuals of malignant and benign oncological diseases.

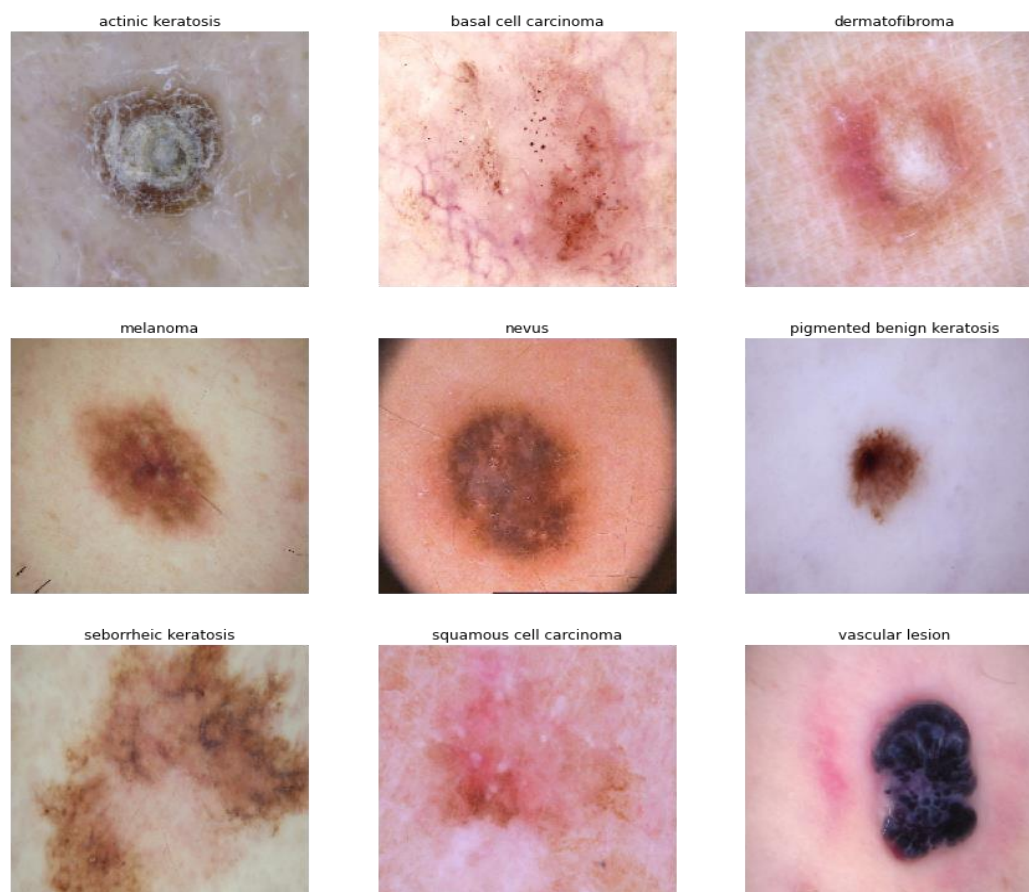


Figure 1. Visuals of Malignant and Benign type oncological diseases

As the rate of melanoma, cases are increasing every day. The survey shows that nearly 21.8 percentage of people around the age of 54-64 are affected in the maximum range and 0.6 percentage of people are affected in less than 20 age. Figure 2 shows the percentage of news melanoma cases detected based on various age level.

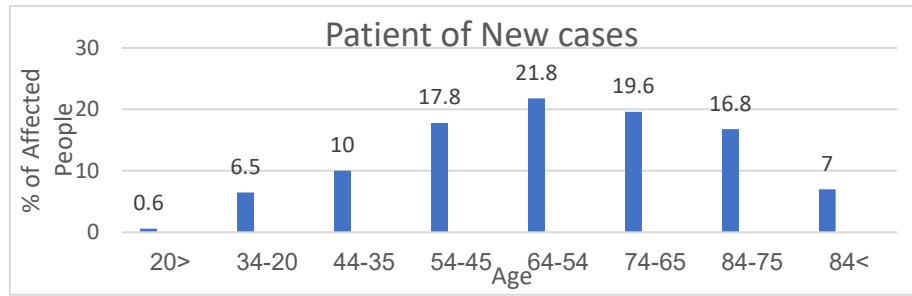


Figure 2. Percentage of news melanoma cases detected based on various age level.

B. Data Processing

Data consists of noise; in Order to remove Background Noise, filters are used to remove the Noise. To overcome the issue that caused the class imbalance in data sets, the data Sets were added by Data Augmenter process and rescaled according to the need. This Process resulted that none of the classes have very few samples. The entire dataset preparation process is illustrated in Figure 3.



Figure 3. Data Processing

C. Convolutional Neural Networks (CNNs)

Convolutional neural networks (CNNs) are well known for its exceptional performance using Input Data like images, speech, or audio signals. There are three different layers present, they are Convolutional layer, Pooling layer and fully connected (FC) layer.

The Very first and important layer in a CNN is the Convolution layer. The next layer is the extra convolutional layers or pooling layers, while the final layer is the fully connected, which produces the output. With each layer, the complexity of the CNN increases, enabling it to identify larger sections in the Data image. The starting layers mainly focus on basic features, such as colors, shapes and edges, while subsequent layers recognize shapes that are more complex and patterns, ultimately identifying the required object.

The convolutional layer Forms is the main and core component of a CNN and it is where most of the computation happens. It requires many components like input data, a selective filter, and a feature map for feature extraction. For example, it consists of a 3D matrix representation of pixels, reflecting height, width, and depth, corresponding to the RGB channels of a color image. A feature detector, which is known as a kernel or filter, that moves across the individual fields of the Data image to check for the presence of features. This Detailed process is termed as convolution.

The Kernel feature detector consists of a two-dimensional (2-D) array of its weights, representing each parts of the image. Where filter sizes can be varied as required, a typical size is commonly a 3x3 matrix, which defines the receptive field's Size. The filter is usually applied to specific region of the processed image, and the dot product is obtained by calculating between the input pixels of the image and the filter values. This dot product obtained is finally placed into an output array. The filter is shifted by striding and this process is repeated until it has covered the entire parts of the image. The final output, which is generated from the series of dot products, is referred to as a convolved feature, feature map, or activation map.

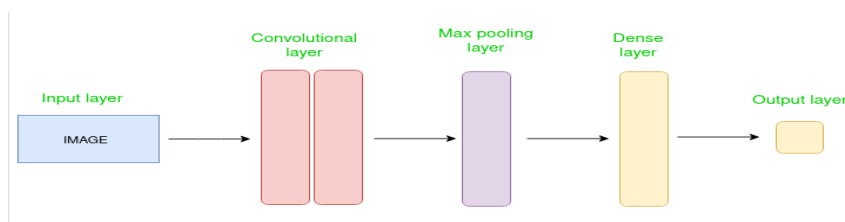


Figure 4. General Steps in Convolution Neural Networks (CNNs)

4. Proposed Methodology

Convolutional Neural Networks (CNNs) Method is one main type of Deep Learning techniques, which is very effective in processing of grid-like data the input images. CNNs consists of Convolution layers, Number of pooling layers, and finally the fully (completely) connected layers which extracts the hierarchical features from pre-processed input image. It is mainly used for object detection, image classification. In this Paper, we propose CNN architecture that will discuss its structure, layer composition, and working mechanism. The architecture is mainly designed to improve its performance and Detection and Classifying accuracy for a given image classification Raw image is applied to the input layer, in the form of image pixels. For a 2D image, the input color image is with a resolution of 128*128 pixels, the inputs to the CNN is 128*128*3.

The Main operation in CNNs is the convolution operation. It consists of filters known as Kernels which is responsible for extracting the features like corners, Edges, patterns and textures

The filter that slides over the input, and performs a dot product between the input pixels of the image and filter values selected. The output is added together and passed through a Relu, which is an activation function. The input unit is set to 0 with a frequency of rate at which each step during training period, which helps to overcome overfitting issues by the Dropout Layer. Next the Flattening layer which will convert the data into a 1-dimensional array as a input to the Dense layer. The dense layer is a one-type neural network layer, which is connected deeply as each of these neurons in the dense layer receives input from all neurons from its previous layer.

Activation Function (ReLU): The Rectified Linear Unit (ReLU) is the most commonly used activation function in CNNs. ReLU improves and accelerates training mechanism and introduces non-linearity Function. It also takes care of degrading gradient Problem resulting in fast training of Deeper Networks.

The pooling layer is responsible for Sub-sampling/ down sampling the feature maps, that reduces their spatial dimensions. It also helps in risk of overfitting and thus reducing the computational complexity.

After number of convolutional and pooling layers, the important high-level features that are extracted are flattened into a single one-dimensional vector and finally, fed into fully connected layers. Each neuron present in these layers are connected to each neuron in the previous layer, allowing the softmax layer to predict the final output. Proposed Methodology of CNN is illustrated in Figure 5.

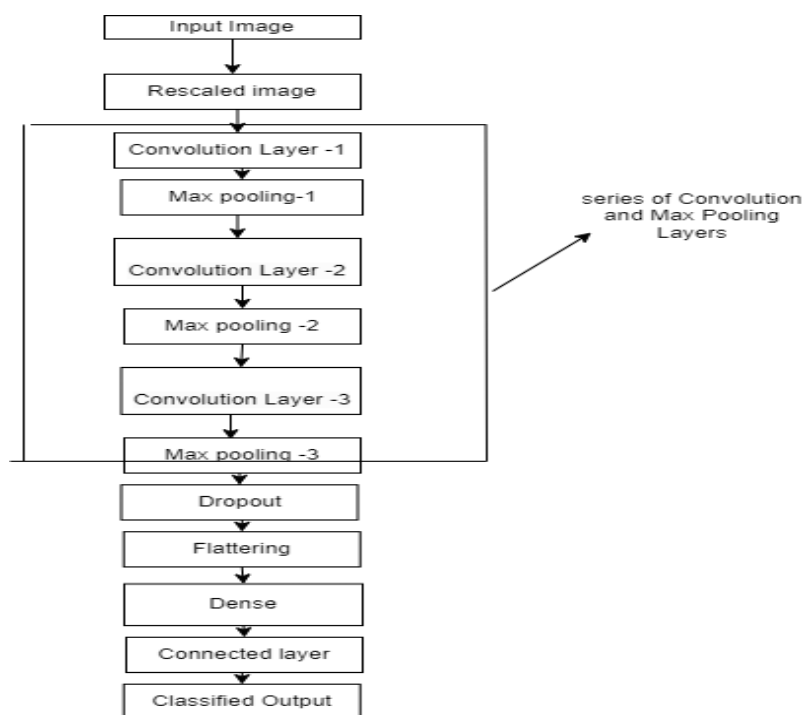


Figure 5. Proposed Methodology

Sensitivity and specificity are critical indicators of test accuracy that help healthcare providers evaluate the effectiveness of diagnostic tools. Sensitivity refers to the proportion of true positive tests among all patients who have the condition. Specificity indicates the percentage of true negatives among all subjects who do not have the disease. Negative Predictive Value (NPV) assesses how many of the negative findings are true negatives, while

Positive Predictive Value (PPV) measures how many of the positive findings are true positives. Accuracy represents the percentage of image pixels that are correctly classified. The F1 score is defined as a machine learning evaluation metric that combines recall and precision to assess a model's accuracy. This score reflects how often the model made correct predictions across the entire dataset.

$$Sensitivity = \frac{TP}{TP+FN} \tag{1}$$

$$Specificity = \frac{TN}{FP+TN} \tag{2}$$

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

$$Negative Predictive Value = \frac{TN}{TN+FN} \tag{4}$$

$$False positive Rate = \frac{FP}{FP+TN} \tag{5}$$

$$Accuracy = \frac{TP+TN}{P+N} \tag{6}$$

$$F1\ Score = 2TP / (2TP + FP + FN) \tag{7}$$

where TP- True positive value, FN- False Negative value, TN- True Negative Value, FP- False Positive value.

5. Results and Discussions

In the Melanoma detection, using CNNs the data was pre-processed and augmented to produce each number of Datasets in each of the Training phase. These Data was sent to 3 layers of Convolution and Max-pooling layers to train the model for validation process.

During the training phase, the accuracy of the proposed model was plotted against the number of epochs. Our findings indicate that the model's accuracy improved gradually over several epochs, highlighting the network's ability to learn as it adjusted its parameters through backpropagation. Notably, the model achieved a high accuracy of 80.80% after a predetermined number of epochs, at which point the accuracy began to plateau. This trend suggests that additional training may yield diminishing returns and that the model has adequately learned the relevant features for classification.

This trend is further illustrated in a plot of loss versus epochs, which underscores the model's gradual improvement in predictions. However, after a certain point, the loss curve began to level off, indicating that the model had reached its peak performance during training. Monitoring the loss is crucial for detecting potential overfitting, which is particularly important in machine learning applications, especially within the medical field. All experiments were executed on a Google Colab. The loss and Accuracy graphs are shown in Figure 4.

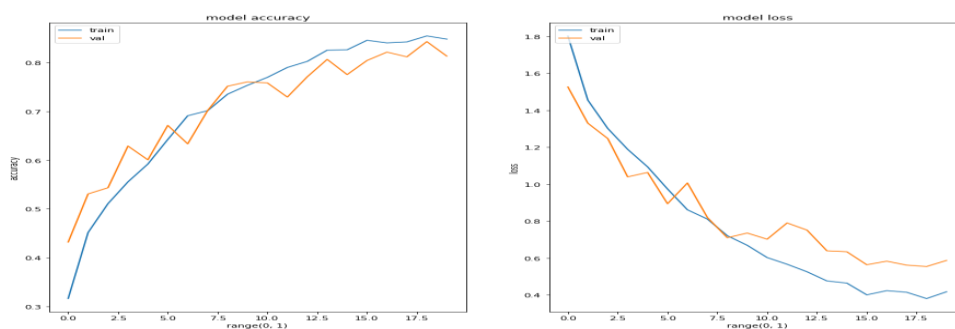


Figure 4. Accuracy versus Epochs and Loss versus Epochs

The results obtained for various parameters obtained are tabulated in the Table 1.

Table 1: Results with Various Parameters

| Measure | Values |
|---------------------------|--------|
| Sensitivity | 0.0943 |
| Specificity | 0.8926 |
| Precision | 0.0943 |
| Negative Predictive Value | 0.8926 |

| | |
|---------------------|--------|
| False Positive Rate | 0.1074 |
| False Negative Rate | 0.9057 |
| Accuracy | 0.8080 |
| F1 Score | 0.0943 |

The Confusion Matrix consists of TP, FP, TN, FN which is obtained for a given balanced dataset, with same numbers of examples in both the classes, The Quality of the Model can be measured by Accuracy, which Serves as the most important and valid metrics. Accuracy acts as the default evaluation metric in generic or unspecified models producing valid generic or unspecific task output. The Confusion Matrix is shown in Figure 5.

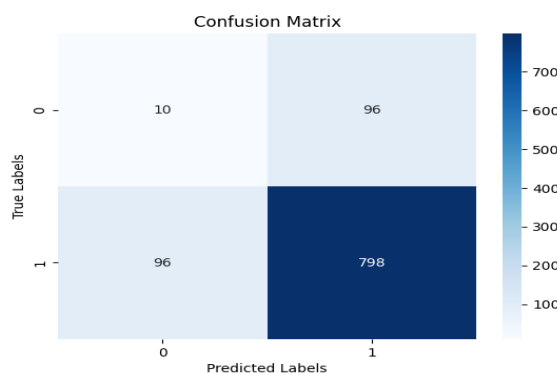


Figure 5. Confusion Matrix

6. Conclusion

In this paper, we introduced a naive solution for Automated Melanoma Detection and classification in Early Stages. The system has a potential to Detect Melanoma, which can help to overcome Traditional diagnostic methods, such as Physical visual examination and biopsy, are tedious and time-consuming and take more time, which can influence patient health. To overcome this problem, the study explores the utilization of deep learning techniques, mainly Convolutional Neural Networks (CNNs), for the automated detection and classification of melanoma Skin Cancer. By Using the ISIC dataset, the proposed model demonstrates a 80.80% of accuracy and efficiency in distinguishing between malignant melanoma (cancerous) and benign skin lesions (non- cancerous). This technique not only reduces the diagnostic process but also increases the speed, Accuracy and precision of melanoma detection and Contribution. Finally contributing to better survival rates of patients and improving healthcare solutions outcome. As part of future work, we aim to integrate Hybrid Modelling approaches to improve the Accuracy.

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