Preprocessing the Skin Cancer Images using Segmentation and Implement Using CNN

Mrs. A. NANDHINI MCA,(PhD)
Assistant Professor, Department of Computer Applications , Nehru College Of Management Coimbatore

Ms. SNEHA R,
II MCA Department of Computer Applications, Nehru College Of Management Coimbatore

ABSTRACT - Skin cancer is one of the most rapidly spreading illnesses in the world and because of the limited resources available. Early detection of skin cancer is crucial accurate diagnosis of skin cancer identification for preventive approach in general. Detecting skin cancer at an early stage is challenging for dermatologists, as well in recent years, both supervised and unsupervised learning tasks have made extensive use of deep learning. Convolutional Neural Networks (CNN), algorithm is used for object detection and classification tests. The dataset used is HAM10000 which consists of seven different types of skin lesions with the sample size of 10015 is used for the experimentation. The data pre-processing techniques like sampling, dull razor and segmentation using auto encoder and decoder is employed. Transfer learning techniques like DenseNet169, Mobile Net were used to train the model to obtain the results.

INDEX TERMS Skin cancer; CNN; DenseNet169; Mobile Net; HAM10000 dataset.

I.INTRODUCTION

A Cancer is a large group of diseases that can start in almost any organ or tissue of the body when abnormal cells grow uncontrollably, go beyond their usual boundaries to invade adjoining parts of the body and/or spread to other organs. The latter process is called metastasizing and is a major cause of death from cancer. A neoplasm and malignant tumour are other common names for cancer. Cancer is the second leading cause of death globally, accounting for an estimated 9.6 million deaths, or 1 in 6 deaths, in 2018. Different types of cancer mainly are Lung, Skin, Breast, Brain etc.[9] Skin cancer is one of the most common types of cancer that begins with the uncontrolled reproduction of skin cells. It can occur because of the ultraviolet radiation from sunshine or tanning beds, and it causes skin cells to multiply and form malignant tumors. There are mainly seven types of skin cancer[9,10]Skin cancer is one of the primary reasons for deaths worldwide. Melanoma is one of the most common and dangerous types of skin cancer that can spread quickly to other body parts. Approximately 21 out of 100,000 melanoma cases were diagnosed in the United States between 2016 and 2020. The death rate because of melanoma was 2.1 per 100,000 diagnosed cases, and 1,413,976 people were living with melanoma in 2020. The number of deaths because of skin melanoma can be reduced if it is detected at its early stages. Automated detection of melanoma is comprised of various steps including preprocessing, extracting region of interest, postprocessing, and finally segmentation[10]For proper classification of skin cancer we use the image processing technique. By using image processing, we can easily find the type of skin cancer. Digital Image processing is the process of transforming an image into a digital form and performing certain operations to get some useful information from it. The image processing system usually treats all images as 2D signals when applying certain predetermined signal processing methods[4] Digital image processing plays an important role in skin cancer classification. Applications of Digital image processing:

Deep learning uses neural networks to learn useful representations of features directly from data. For example, you can use a pretrained neural network to identify and remove artifacts like noise from images[3] A neural network is a method in artificial intelligence that teaches computers to process data in a way that is inspired by the human brain. It is a type of machine learning process, called deep learning, that uses interconnected nodes or neurons in a layered structure that resembles the human brain. It creates an adaptive system that computers use to learn from their mistakes and improve continuously[3,7] Thus, artificial neural networks attempt to solve complicated problems, like summarizing documents or recognizing faces, with greater accuracy. There are mainly three layers in neural network : input layer, hidden layer and output layer. CNN is a type of neural network. A Convolutional Neural Network (CNN) is a type of deep learning algorithm specifically designed for image processing and recognition tasks[8] The CNN architecture comprises three main layers: convolutional layers, pooling layers, and a fully connected (FC) layer. Object detection and bracket tasks are ben dominated by Convolutional Neural Networks (CNN) As a result, trained end-to-end in a controlled environment, CNNs eliminate the need for humans to manually create feature sets. The use of Convolutional Neural Networks (CNNs) to categorize lesions in skin cancer in recent years has outperformed skilled mortal specialists[8,11]

LITERATURE REVIEW

Although the advancement in the dermatological equipment has increased the classification accuracy of melanoma, the technological developments and improvements in the area of deep learning and image processing have resulted in a medical breakthrough in diagnosis, detection, and classification of skin lesions with much more accuracy and reliability[4] The literature review reveals that different practices have been used to develop computer-aided automatic diagnostics systems for the classification of skin cancer which take dermoscopic images as input and give classification results as output. “Deep Learning for Skin Cancer Classification: A Comprehensive Review” by Esteva et al.(2019)[6] This review paper provides a comprehensive overview of deep learning methods for skin cancer classification. It covers various aspects such as datasets, network architectures, and performance evaluation metrics.“Skin Lesion Classification Using Deep Learning Techniques” by Han et al. (2020)[2]This paper explores the application of different deep learning techniques for skin lesion classification. It discusses the use of convolutional neural networks (CNNs), transfer learning, and data augmentation strategies.“Skin Cancer Detection Using Deep Learning” by Maryam Naqvi.(2023)[3]Skin cancer is one the most dangerous types of cancer and is one of the primary causes of death worldwide. This paper reviewed the most recent research articles on skin cancer classification using deep learning methods. We also provided an overview of the most common deep-learning models and datasets used for skin cancer classification.“Dermatologist-level Classification of Skin Cancer with Deep Neural Networks” by Esteva et al. (2017)[7]In this paper, the authors demonstrate the effectiveness of deep neural networks in classifying skin cancer. They trained a CNN on a large dataset of dermatoscopic images and achieved performance comparable to dermatologists.This systematic review evaluates the current state-of-the-art in skin cancer classification using CNNs. It analyzes the strengths and weaknesses of existing methods and identifies areas for future research.“DeepSkin: A Deep Learning Approach for Skin Cancer Classification” by H. L. GURURAJ 1 , (Senior Member, IEEE)[4] Skin cancer is one of the most rapidly spreading illnesses in the world and because of the limited resources available. Early detection of skin cancer is crucial accurate diagnosis of skin cancer identification for preventive approach in general. Detecting skin cancer at an early stage is challenging for dermatologists, as well in recent years, both supervised and unsupervised learning tasks have made extensive use of deep learning.Convolutional neural networks learn directly from data and are widely used for image recognition and classification. The methods in this paper included training the model with the help of CNN and obtained an accuracy of 78%[8] We have utilized HAM10000 Dataset for the training and validation in this study. HAM10000 dataset is a benchmark dataset with over 50% of lesions confirmed by pathology.The main goal of this study is to categorise skin lesions using Deep learning, especially using the CNN method.[12] The purpose of this research is to find improved and more effective ways to detect skin cancer using digital image processing and Deep learning techniques.[1,5] The final objective is to assist the doctors in the detection of skin cancer at an early stage by providing improved and reliable results.

III. METHODOLOGY

Detecting skin cancer at an early stage is challenging for dermatologists. In this paper we use Deep learning approaches for classification of skin cancer images. Deep learning methods like Convolutional Neural Networks (CNN), has surpassed all others in object detection and classification tests. In figure 1 shows the seven types of skin cancer.various types of skin cancer are: Nevus, Dermatofibroma, Melanoma, Acitinic keratosis, Benign keratosis, Basal cell Carcinoma, Vascular etc..With the extensive use of deep learning procedures as shown in Figure2 helps to classify the seven types of skin cancer images.

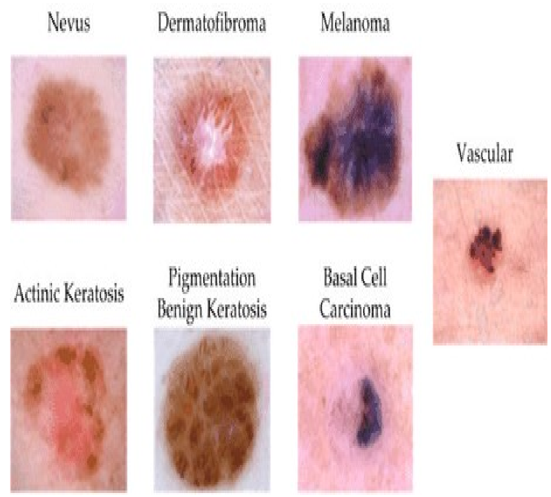

Figure 1. classification of skin c

A. DATASET DESCRIPTION

In this paper we use HAM10000 dataset for classification of skin lesions into seven different classes. The HAM10000 training set includes 10,015 dermoscopic images for detecting pigmented skin lesions. This dataset is publicly available through the ISIC archive. HAM10000 includes 142 images of vascular skin lesions, 327 images of AK, 514 images of basal cell carcinomas, 1099 images of benign keratoses, 115 images of dermatofibromas, 1113 images of melanocytic nevi, and 6705 images of melanomas. Various other dataset are:PH2, ISIC 2016-2020.

B. DATA VISUALIZATION

Data preprocessing is the concept of changing raw data into clean dataset. The dataset is preprocessed in order to check missing values, noisy data, and other inconsistencies before executing it to the algorithm.

Some common steps in data preprocessing include: Data cleaning, Data Integration,Data Transformation, Data Reduction,Data Discretion,Data Normalization. The visual presentation of information and data is known as data visualization. Figure 3. shows the graphical representation of data visualization of the skin lesions we can use a technique called sampling to balance the dataset. Sampling in skin cancer classification involves selecting a representative subset of skin lesion images from a larger dataset for training, validation, and testing purposes. There are mainly two techniques is used in sampling for balance the dataset. They are oversampling and under sampling

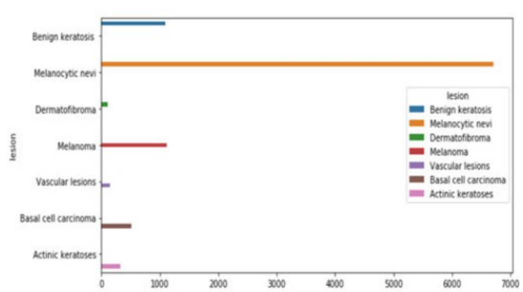

Figure 3. Data Visualization

Over sampling(up sampling):Oversampling involves increasing the number of instances in the minority class or classes to balance the class distribution. The most common technique for oversampling is duplication, where existing instances from the minority class are duplicated or replicated to match the size of the majority class. Other techniques include generating synthetic samples using methods like Synthetic Minority Over-sampling Technique (SMOTE) or Adaptive Synthetic Sampling(ADASYN).Under sampling(Down sampling) : Under sampling involves reducing the number of instances in the majority class to match the size of the minority class or classes. The simplest under sampling technique is random under sampling, where instances from the majority class are randomly removed until the class distribution is balanced. Under sampling can also be done in a more strategic manner, such as selecting instances that are most similar to those in the minority class or using clustering techniques to identify representative subsets of the majority class..

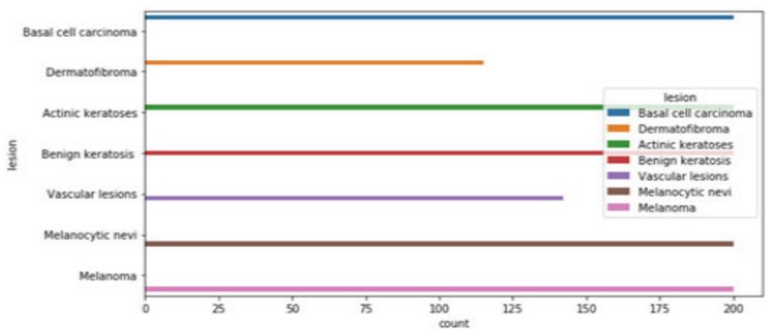

Figure 4. shows the balanced dataset of the skin lesions to the respective classes they belong to

C.REMOVING THE NOISE FROM THE SKIN IMAGE.

Removing noise from skin lesions typically refers to the process of enhancing the quality of images containing skin lesions by reducing unwanted artifacts or disturbances while preserving important features. The Dull Razor method can be used to remove hair from skin images. Dull Razor takes the following actions:

1. The dark hair locations are identified by the use of a generalized grayscale morphological closing technique.
2. A bilinear interpolation is used to replace the hair pixels that have been verified as having a thin and long structure.
3. To smooth out the hair pixels that have been replaced, it uses an adaptive median filter. Let Gt represent the original band's generalized grayscale closure pictures, and Ot , S1, S2, and S3 represent the horizontal, vertical, and diagonal structure elements. Gt can be written as given in equation (1)

$$Gt = |Ot - \max\{Ot \cdot S1Ot \cdot S2Ot \cdot S1\}| \qquad (1)$$

where · indicates that the operation is in grayscale. Furthermore, for the coordinates (x, y), Mr (x, y), the binary hair mask pixel is computed as shown in equation (2)

$$Mr (x, y) = 1, \text{ if } Gr (x, y) > T = 0, \text{ otherwise} \quad (2)$$

where T is a predefined threshold value. For green and blue channels, we may use a phrase like that. It's the aggregate of the three-color channels' hair masks that makes up the final mask for the original image, M as given in equation (3).

$$M=Mr \cup Ma \cup Mb \quad (3)$$

The hair masks for the appropriate color channels are Mr , Ma, and Mb. Due to the thresholding procedure and image noise, it is difficult to determine exactly where the borders are in the image. It is common to produce tiny lines around the hair region's boundary. The thin lines are smoothed out using an adaptive median filter in this step. Figure 5. shows the removal of hair from the skin Lesions

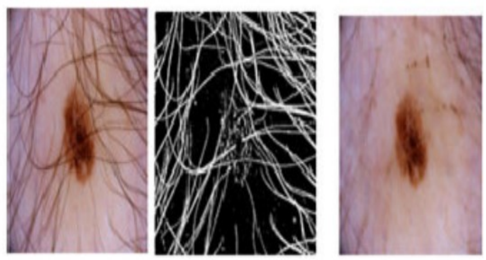

Figure 5. Removal of hair from skin lesion

D. SEGMENTATION OF IMAGE

Segmentation of images refers to the process of partitioning an image into multiple segments or regions based on certain criteria, such as color, intensity, texture, or other features. Image segmentation is a fundamental task in computer vision and has various applications, including object detection, image recognition, medical image analysis, and scene understanding. The encoder and decoder technology are used to segment images for biomedical image segmentation.

ENCODER:The encoder portion of the architecture consists of convolutional layers followed by downsampling operations such as max-pooling or strided convolutions. These layers progressively reduce the spatial dimensions of the input image while increasing the number of feature channels. This process helps in extracting high-level features and spatial information from the input image. DECODER: The decoder portion of the architecture is responsible for upsampling the encoded features to the original input resolution and generating the segmentation mask. It typically consists of upsampling layers (such as transposed convolutions or bilinear upsampling) followed by convolutional layers. The decoder progressively refines the spatial resolution while reducing the number of feature channels to produce the final segmentation output.

IV. SYSTEM IMPLEMENTATION

Convolutional Neural Networks (CNNs) are built in such a way that they can account for the input's spatial structure. They were originally developed to work with images and were inspired by the visual system of the mouse.A Convolutional Neural Network_(CNN) is a type of deep learning algorithm that is particularly well-suited for image recognition and processing tasks. It is made up of multiple layers, including convolutional layers, poolinglayers, and fully connected layers. The architecture of CNNs is inspired by the visual processing in the human brain, and they are well-suited for capturing hierarchical patterns and spatial dependencies within images. Pre-trained models like Densenet169 and mobile Net were used to make a comparison study between oversampling and undersampling technique. Mobile Net is a computer vision model open-sourced by Google and designed for training classifiers. It uses depthwise convolutions to significantly reduce the number of parameters compared to other networks, resulting in a lightweight deep neural network. The accuracy of the model obtained is 91.2%. In order to examine learning, generalizing and performance of the model, we computed training-validation loss curve (Figure 6(a) and training-validation accuracy curves for categorical (Figure 6(b)), top2 (Figure 6(c)) and top3 (Figure 6(d)) accuracies. The model shows a good learning rate as the training accuracy increase with the number of 12 iterations along with symmetric downward sloping of the training loss curve. The small gap between training and validation curves represents a good-fit, showing model can generalize well on unknown images.Python is a general purpose, dynamic, high level, and interpreted programming language. It supports Object Oriented programming approach to develop applications. It is simple and easy to learn and provides lots of high-level data structures.Python is easy to learn yet powerful and versatile scripting language, which makes it attractive for Application Development.

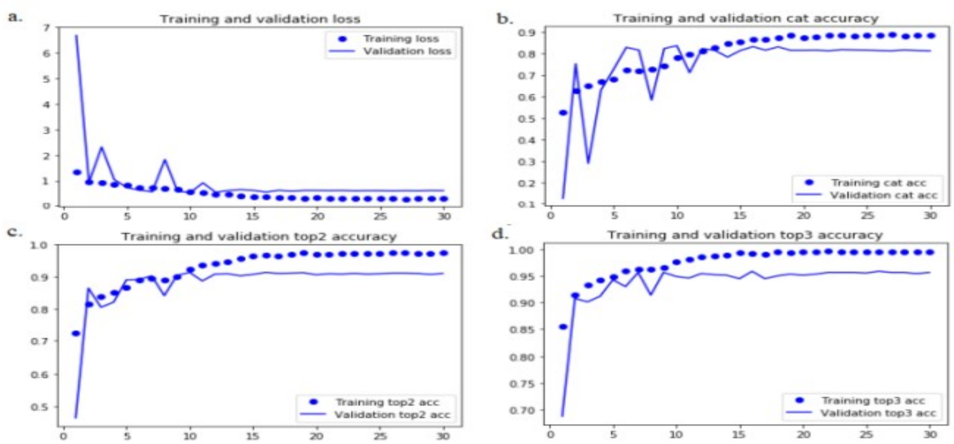

Figure 6.Skin cancer classification performance curves of MobileNet model (a) Training and Validation loss (b) Training and Validation categorical accuracy (c) Training and validation top2 accuracy (d) Training and Validation top3 accuracy

EVALUATION METRICS

The overall performance of the model was evaluated with several evaluation metrics: Accuracy, Micro Average of Precision (MAP), Micro Average of Recall (MAR), and Micro Average of F1-score (MAF). The weighted average for Recall, Precision, and F1-score was evaluated by using the following mathematical expressions.

VII. CONCLUSION

The skin cancer incidences are intensifying over the past decades; the need of an hour is to move towards an efficient and robust automated skin cancer classification system, which can provide highly accurate and speedy predictions. Additionally, dermatologists have trouble seeing skin cancer in its early stages. In this study, we demonstrated the effectiveness of deep learning in automated dermoscopic skin cancer classification with the Mobile-Net model trained on a total of 38,569 dermoscopy images from HAM10000 dataset. We matched the performance of expert dermatologists across seven diagnostic tasks with an overall accuracy of 83.1% for seven classes in the dataset, whereas top2 and top3 accuracy of 91.36% and 95.34%, respectively. Also, the weighted average of precision, the weighted average of recall, and the weighted average of f1-score were found to be 89%, 83%, and 83%, respectively. We conclude that Mobile-Net model can be used to develop an efficient real-time computer-aided system for automated medical diagnosis systems.

REFERENCES

[1] Y. C. Lee, S.-H. Jung, and H.-H. Won, "WonDerM: Skin lesion classification with fine-tuned neural networks," 2018, arXiv:1808.03426

[2] Han et al. "Skin Lesion Classification Using Deep Learning Techniques" (2020)

[3] American Cancer Society. Cancer Facts & Figures. 2021. [accessed 2021 September 3]. Available from:

[4] International Skin Imaging Collaboration. The ISIC 2020 Challenge Dataset. ISIC; 2020. Available from:

[5] C.Nagarajan and M.Madheswaran - 'Experimental verification and stability state space analysis of CLL-T Series Parallel Resonant Converter' - Journal of ELECTRICAL ENGINEERING, Vol.63 (6), pp.365-372, Dec.2012.

[6] C.Nagarajan and M.Madheswaran - 'Performance Analysis of LCL-T Resonant Converter with Fuzzy/PID Using State Space Analysis'- Springer, Electrical Engineering, Vol.93 (3), pp.167-178, September 2011.

[7] C.Nagarajan and M.Madheswaran - 'Stability Analysis of Series Parallel Resonant Converter with Fuzzy Logic Controller Using State Space Techniques'- Taylor & Francis, Electric Power Components and Systems, Vol.39 (8), pp.780-793, May 2011.

[8] C.Nagarajan and M.Madheswaran - 'Experimental Study and steady state stability analysis of CLL-T Series Parallel Resonant Converter with Fuzzy controller using State Space Analysis'- Iranian Journal of Electrical &Electronic Engineering, Vol.8 (3), pp.259-267, September 2012.

[9] Nagarajan C., Neelakrishnan G., Akila P., Fathima U., Sneha S. "Performance Analysis and Implementation of 89C51 Controller Based Solar Tracking System with Boost Converter" Journal of VLSI Design Tools & Technology. 2022; 12(2): 34–41p.

[10] C. Nagarajan, G.Neelakrishnan, R. Janani, S.Maithili, G. Ramya "Investigation on Fault Analysis for Power Transformers Using Adaptive Differential Relay" Asian Journal of Electrical Science, Vol.11 No.1, pp: 1-8, 2022.

[11] G.Neelakrishnan, K.Anandhakumar, A.Prathap, S.Prakash "Performance Estimation of cascaded h-bridge MLI for HEV using SVPWM" Suraj Punj Journal for Multidisciplinary Research, 2021, Volume 11, Issue 4, pp:750-756

[12] G.Neelakrishnan, S.N.Pruthika, P.T.Shalini, S.Soniya, "Perfromance Investigation of T-Source Inverter fed with Solar Cell" Suraj Punj Journal for Multidisciplinary Research, 2021, Volume 11, Issue 4, pp:744-749

[13] C.Nagarajan and M.Madheswaran, "Analysis and Simulation of LCL Series Resonant Full Bridge Converter Using PWM Technique with Load Independent Operation" has been presented in ICTES'08, a IEEE / IET International Conference organized by M.G.R.University, Chennai.Vol.no.1, pp.190-195, Dec.2007

[14] M Suganthi, N Ramesh, "Treatment of water using natural zeolite as membrane filter", Journal of Environmental Protection and Ecology, Volume 23, Issue 2, pp: 520-530,2022

[15] M Suganthi, N Ramesh, CT Sivakumar, K Vidhya, "Physiochemical Analysis of Ground Water used for Domestic needs in the Area of Perundurai in Erode District", International Research Journal of Multidisciplinary Technovation, pp: 630-635, 2019.