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Detection of Melanoma Skin Cancer using Deep Learning

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***Abstract**:* The primary objective of this project is to design a robust deep learning model that is capable of accurately identifying melanoma lesions from dermoscopic images. The Melanoma is a type of skin cancer, which, if detected in its early stages, is highly curable. But its detection is hard, even under expert supervision. This paper is an attempt to make detection of Melanoma using deep learning techniques more efficient and reliable compared to existing techniques. The overall approach followed is to build a two-stage network. The first-stage network targets accurate segmentation of the skin lesion, from the actual dermoscopic images. The second-stage network is a classification network to predict the presence of Melanoma in the sample. For the segmentation stage network, both the U-NET and FCRN methods were implemented. For the classification network, the DRN architecture was implemented. In order to enhance the achieved results, the step-decay technique to modify learning rates was used. Using both binary cross-entropy and weighted binary cross-entropy improved the achieved results, driving towards better accuracy of detection. Convolutional Neural Networks (CNNs) will be employed for feature extraction and classification, leveraging their ability to automatically learn hierarchical representations from image data. The evaluation of the model's performance will be conducted using standard metrics such as sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). Comparative analyses with existing melanoma detection methods will also be performed to showcase the proposed system's effectiveness.

IndexTerms – dermoscopic,fcrn methods,deep learning techniques

I. INTRODUCTION

Skin cancer is a typical common cancer. Melanoma, also known as malignant melanoma, is the most lethal form of skin cancer and responsible for 75% of skin cancer deaths, despite being the least common skin cancer. The best way to combat that is trying to identify it as early as possible and treat it with minor surgery. The experimental evaluations on a large publicly available dataset ISIC 2020 Challenge Dataset, which is generated by the International Skin Imaging Collaboration and images of it are from several primary medical sources, have demonstrated state-of-the-art classification performance compared with prior popular melanoma classifiers on the same dataset.

Deep learning is a method in artificial intelligence (AI) that teaches computers to process data in a way that is inspired by the human brain. Deep learning models can recognize complex patterns in pictures, text, sounds, and other data to produce accurate insights and predictions. The deep leaning majorly involves of three techniques.

Early detection of melanoma is crucial for effective treatment and improved survival rates. However, differentiating malignant melanoma from benign skin lesions can be challenging, even for experienced dermatologists. Traditional diagnostic methods include visual inspection with the aid of dermoscopy, followed by biopsy and histo pathological examination. These methods, while effective, are time-consuming and subject to inter-observer variability, leading to a demand for more objective, accurate, and efficient diagnostic tools.

Deep learning, a subset of machine learning based on artificial neural networks, has shown remarkable success in various fields of image analysis and pattern recognition, including medical imaging.

Convolutional Neural Networks (CNNs), in particular, have demonstrated high performance in tasks involving visual data due to their ability to automatically learn and extract hierarchical features from raw images. This capability makes CNNs a promising tool for medical image analysis, including the detection and classification of skin lesions.

II. RELATED WORK

In this paper, the systematical study of melanoma is noticed by using deeper, wider and higher resolution convolutional neural networks can obtain better performance to detect the melanoma. The experimental evaluations on all the available dataset ISIC 2020 Challenge Dataset, which is generated by the International Skin Imaging Collaboration and images of it are from several primary medical sources The classification and segmentation results are shown using a GUI. The idea to classify the melanoma using shearlet transform coefficients and naïve Bayes classifier. The datasetis decomposed using shearlet transform (efficient algorithm implementations) with the predefined number of (50, 75 and 100) it. Here for skin cancer classification, dermo- scopic images were employed to Deep CNN architecture to extract deep features for classification of melanoma into cancer\malignant type and benign/non- cancerous type.

The perception of skin disease is accomplished through two phases. Phase I involves collection and preprocessing of dataset and the training phase and the testing phase of the developed Deep CNN model. Phase II includes real time implementation and visualization of result in GUI. Since one of the factors that determines the accuracy of prediction is the database, at least six different databases which is collected, different physicians/researchers/medical students/pathologists/competitions. Also, for each image in the database, the manual segmentation and the clinical diagnosis of the skin lesion as well as the identification of other important dermo-scopic criteria is available.

The literature on the detection of melanoma skin cancer using deep learning has grown substantially in recent years, reflecting the field's rapid advancements and the critical need for accurate diagnostic tools. Early research focused on traditional image processing techniques and machine learning algorithms, which required extensive feature engineering and often struggled with generalizability across diverse datasets. With the advent of Convolutional Neural Networks (CNNs), there has been a significant shift towards deep learning approaches, which excel in automatically learning hierarchical features directly from raw images. Pioneering studies by Esteva et al. (2017) demonstrated that deep learning models could achieve dermatologist-level accuracy in melanoma classification using large, annotated datasets. Subsequent research has explored various CNN architectures, such as VGG, ResNet, and Inception, with modifications tailored to improve sensitivity and specificity in detecting melanoma. Advanced techniques, including transfer learning and data augmentation, have further enhanced model performance, particularly when dealing with limited labeled data. Recent efforts have also focused on improving the interpretability of these models using methods like Grad-CAM and saliency maps, ensuring that the decision- making process is transparent and clinically meaningful. Despite these advancements, challenges such as dataset biases, the need for large-scale annotated data, and integration into clinical practice remain areas of active research and development. Overall, the literature indicates a promising trajectory for deep learning in melanoma detection, with ongoing innovations aimed at improving diagnostic accuracy and clinical applicability. Recent studies have reported excessive exposure to ultraviolet rays as a major factor in developing skin cancer. The most effective solution to control the death rate forskin cancer is a timely diagnosis of skin lesions as the five-year survival rate for melanoma patients is 99 percent when diagnosed and screened at the early stage. Considering the inability of dermatologists to accurate diagnosis of skin cancer, there is a need to develop an automated efficient system for the diagnosis of skin cancer.In recent years, several classification approaches have been proposed for the automatic detection of skin cancer from dermatoscopic images. CNN approaches have completely dominated the skin lesion classification process and this related work will be just a drop in the bucket.The proposed approaches are evaluated using the HAM10000 dataset taken from the ISIC 2018 challenge, consisting of 10,015 dermatoscopic images belonging to 7 classes, and the ISIC 2019 dataset taken from the ISIC 2019 challenge, consisting of 25,331 dermatoscopic images belonging to 8 classes.Some paper focuses on the importance of the Python programming language. It has interfaces to many operating system calls and libraries and is extensible to C or C++. Many large companies that use the Python programming language include NASA, The subjective weights are designed according to the relative confidence of the classifiers while recognizing a specific previously ‘‘unseen” sample which is calculated by the posterior knowledge obtained through the testing phase. While designing the objective weights, a customizable cost matrix is utilized to enable the ‘ cost-sensitive” feature infusion framework, were given a sample, different outputs of a classifier should result in different costs. In the experimental evaluation, 96 base classifiers are trained as the input of the fusion framework, utilizing twelve CNN architectures on the ISIC Challenge 2019 research dataset for skin image analysis. Two static fusion baseline approaches and two state-of-the-art active fusion approaches are compared with the CS-AF framework. Experimental results show that the CS-AF framework consistently outperforms the static fusion baseline approaches and the state-of-the-art competitors in terms of accuracy, and always achieves lower total cost. Skin lesion images are classified through a deep learning approach with a non- traditional bilinear CNN architecture. The model is trained in a transfer learning and fine-tuning way. The proposed method called BILSK is tested on the HAM10000 dataset. This approach gets the highest accuracy against state- of-the-art techniques in the classification of current skin lessions.

III. PROPOSED SYSTEM

Here for skin cancer classification, dermo-scopic images were employed to Deep CNN architecture to extract deep features for classification of melanoma into cancer\malignant type and benign/non-cancerous type. The perception of skin disease is accomplished through two phases.Phase I involves collection and preprocessing of dataset and the training phase and the testing phase of the developed Deep CNN model. Phase II includes real time implementation and visualization of result in GUI. Since one of the factors that determines the accuracy of prediction is the database, at least six different databases (available online) which is collected by different physicians/researchers/medical students/pathologists/competitions. Also, for each image in the database, the manual segmentation and the clinical diagnosis of the skin lesion as well as the identification of other important dermo-scopic criteria is available.

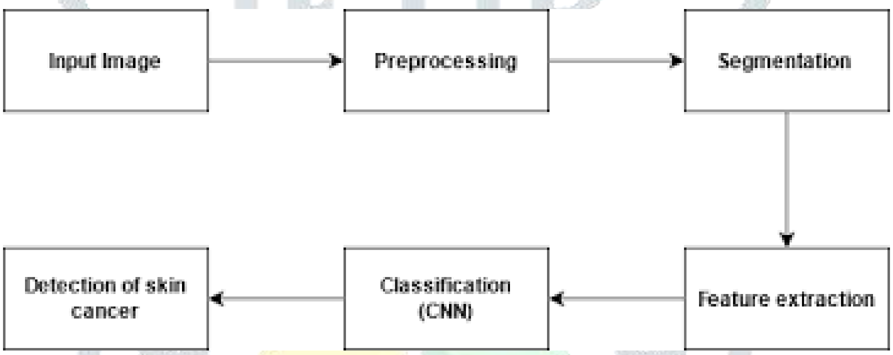

Fig 1 The Block diagram of detection of melanoma

Deep learning can be defined as the method of machine learning and artificial intelligence that is intended to intimidate humans and their actions based on certain human brain functions to make effective decisions. It is a very important data science element that channels its modeling based on data-driven techniques under predictive modeling and statistics. To drive such a human-like ability to adapt and learn and to function accordingly, there have to be some strong forces which popularly called algorithms. Deep learning algorithms are dynamically made to run through several layers of neural networks, which are nothing but a set of decision-making networks that are pre- trained to serve a task. Later, each of these is passed through simple layered representations and move on to the next layer. However, most machine learning is trained to work fairly well on datasets that have to deal with hundreds of features or columns. For a data set to be structured or unstructured, machine learning tends to fail mostly because they fail to recognize a simple image having a dimension of 800x1000 in RGB. It becomes quite unfeasible for a traditional machine learning algorithm to handle such depths. Deep learning has transformed various industries by providing powerful tools for understanding and leveraging complex data, driving innovation.

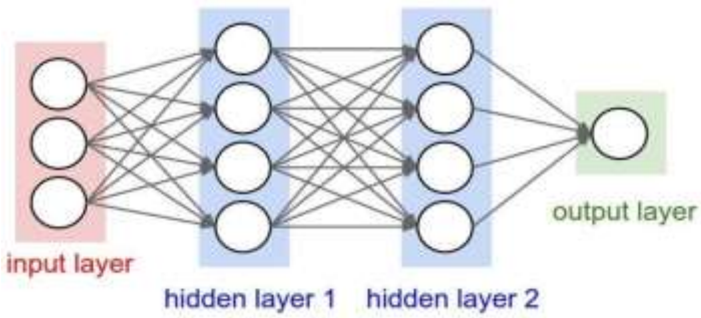

Fig 2 Deep learning Model

Input layers

Input layers in neural networks serve as the entry point for data into the model. They receive raw input data, such as images, text, or numerical features, and pass them through the network for processing. The number of neurons in the input layer corresponds to the dimensions of the input data. For example, in image classification tasks, each neuron may represent a pixel or a feature extracted from the image. Input layers do not perform any computations but simply pass the input data to the subsequent layers. The data is typically normalized or preprocessed before being fed into the network to ensure consistency and convergence during training. The input layer's role is crucial in determining the initial representation of the input data, which is then refined through the network's hidden layers to produce meaningful predictions or outputs.

Hidden layers

Hidden layers in deep learning are intermediate layers between the input and output layers of a neural network. They are responsible for extracting and learning features from the input data through a series of nonlinear transformations. Each hidden layer consists of multiple neurons that perform computations on the input data using weighted connections and activation functions. The number of hidden layers and neurons within each layer is determined by the network architecture and complexity of the task. Hidden layers enable neural networks to capture complex relationships and patterns in the data, facilitating the model's ability to generalize to unseen examples. Training involves adjusting the weights of connections between neurons to minimize the difference between the predicted and actual outputs, allowing the hidden layers to learn increasingly abstract representations of the input data.

Output layers

This method uses a mix of labeled and unlabeled data. It's like having a teacher with some answers but not all. The labeled data helps guide the learning process, especially when there isn't enough labeled data available. This approach is handy when labeling data is expensive or time-consuming.

Fig 3 Flow chart of detection of Melanoma skin cancer

IV. RESULTS

The following figures will propose the detection of melanoma and its accuracy that will be shown from Fig 4 to Fig 12, these figures involves browsing the image, selecting the image, uploading the image and will results the accuracy and the classification of diesaese. The proposed model implements a Flask web application for skin disease classification using a pre-trained Mobile Net model. Upon uploading an image, the application preprocesses it, loads the pre-trained model along with its weights, and makes predictions on the uploaded image. The predicted skin disease class, along with the corresponding accuracy percentage, is then displayed to the user. The application architecture adheres to the Model-View-Controller (MVC) pattern, with routes defined for the home page ('/') and the page to handle uploaded images ('/uploaded'). The pre- trained model is loaded from a JSON file and its weights from an H5 file. The predicted class and accuracy are displayed along with the uploaded image. Additionally, the application utilizes Flask's rendering capabilities to present the results to the user via HTML templates. However, there are a few considerations for improvement. The application currently lacks error handling for cases such as incorrect file types or failed model loading, which could be addressed to enhance robustness. Moreover, optimizing the image preprocessing and model prediction processes could improve the application's performance, especially for handling multiple concurrent requests. Overall, with enhancements in error handling and performance optimization, the application presentsa straightforward and user-friendly interface for skin disease classification.

Fig 4 Framework

Fig 5 Working algorithm

The Fig 4 involes the flask framework interface, the Fig 4 invloves the working of algorithm, Fig 7 involves browsing the image, Fig 8 involves uploading the image and Fig 8 – Fig 10 involves the predicted dieasease and its accuracy.Overall, the output provides a clear and informative summary of the skin disease classification results, allowing users to interpret and assess the model's performance easily.

Fig 6 Browsing the image

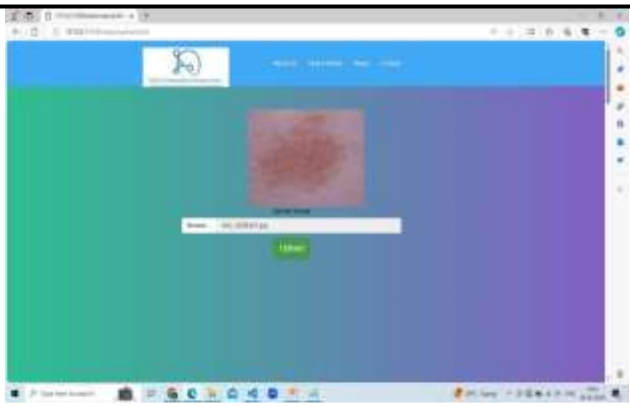

Fig 7 Uploading the image

Fig 8 Output

Fig 9 Lubax algorithm

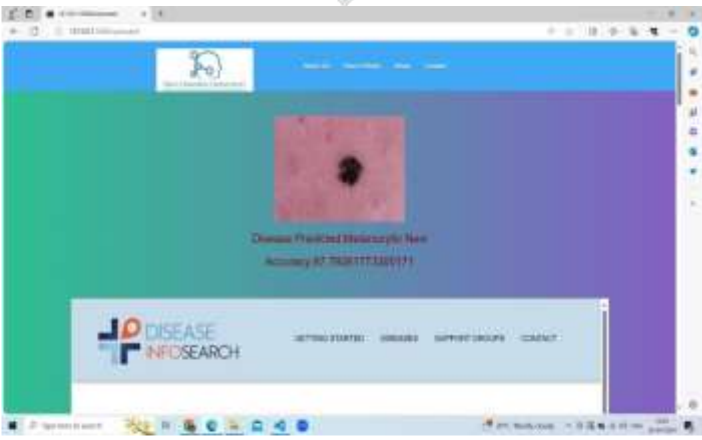

Fig 10 output

V. CONCLUSIONS AND FUTURE SCOPE

The integration of deep learning into melanoma detection represents a significant advancement in medical diagnostics, enhancing early detection, accuracy, and accessibility, especially through telemedicine for remote and underserved populations. This technology supports dermatologists by reducing diagnostic errors and aiding in personalized treatment plans. Additionally, it facilitates public health initiatives through large-scale screening programs and public education on self- monitoring techniques. The efficiency and cost-effectiveness of deep learning systems can lower healthcare costs by enabling early intervention and streamlining diagnostics. Continued research, fueled by extensive dataset analysis, will refine these algorithms, ensuring they remain at the forefront of medical innovation. Moreover, potential integration with wearable technology suggests a future of continuous, real-time health monitoring. This paper compares three pre-trained CNN models—MobileNet, ResNet- 50, and VGG-16—using the HAM10000 and ISIC 2019 datasets. The models achieved promising accuracies, with the best pre-trained model reaching 93.63% on ISIC 2019. The proposed model further improved accuracies to 97.04% and 94.83% on HAM10000 and ISIC 2019 respectively, demonstrating its effectiveness as a tool for accurate skin cancer diagnosis.The future of melanoma detection is promising, with advancements expected in several key areas. AI and machine learning are enhancing diagnostic accuracy, sometimes surpassing dermatologists, and enabling automated screening tools on smartphones. Improved imaging technologies, such as high-resolution imaging and multiphoton microscopy, offer detailed visualization of skin lesions at a cellular level. Genomics and biomarkers research is paving the way for genetic tests and biomarker identification, aiding early detection and personalized monitoring. Wearable technology, like smart wearables and skin patches, could provide real-time monitoring and data analysis. Teledermatology expands access to specialist care through remote consultations, with AI enhancing diagnostic accuracy. Public health initiatives focus on awareness campaigns and preventive programs to educate about early signs and UV protection. Integrating multi-omics data and big data analytics can improve diagnostic precision and early detection. Innovative research and clinical trials are developing new diagnostic methods, promising better outcomes for melanoma patients. Overall, these advancements aim to improve early detection, diagnosis, and patient survival rates.

REFERENCES

[1]. Detection of melanoma in dermo-scopic images by integrating features extracted using handcrafted and deep learning models. Priti Bansal, Ritik Garg, Priyank Soni (2022)

[2]. Multiclass Skin Lesion Classification Using a Novel Lightweight Deep Learning Framework for Smart Healthcare. Long Hoang, Suk-Hwan Lee, Eung-Joo Lee, Ki- Ryong Kwon (2022)

[3]. Multi-class skin lesion classification using prism- and segmentation- based fractal signatures. José Ariel Camacho-Gutiérrez, Selene Solorza-Calderón, Josué Álvarez-Borrego b (2022)

[4]. CS-AF: A cost-sensitive multi-classifier active fusion framework for skin lesion classification. Di Zhuang, Keyu Chen, J. Morris Chang (2022)

[5]. Hierarchy-aware contrastive learning with late fusion for skin lesion classification. Benny Wei-Yun Hsua, Vincent S. Tseng (2022)

[6]. SSD-KD: A self-supervised Diverse Knowledge Distillation Method for Lightweight Skin Lesion Classification Using Dermoscopic Images. Yongwei Wanga, Yuheng Wang, Tim K. Lee, ChunyanMiaog, Z. Jane Wang (2022)

[7]. Optimized Convolutional Neural Network Models for Skin Lesion Classification. Juan Pablo Villa-Pulgari , Anderson Alberto Ruales-Torres, Daniel Arias- Garzón, Mario Alejandro Bravo-Ortiz, Harold Brayan Arteaga-Arteaga, Alejandro Mora-Rubio, Jesus Alejandro Alzate-Grisales, Esteban Mercado-Ruiz , M. Hassaballah , Simon Orozco-Arias, Oscar Cardona-Morales and ReinelTabares-Soto (2021)

[8]. BILSK: A bilinear convolutional neural network approach for skin lesion classification. Camilo Calderon, Karen Sanchez, Sergio Castillo, Henry Arguello (2021)

[9]. Multiclass skin cancer classification using EfficientNets – a first step towards preventing skin cancer. Karar Ali, Zaffar Ahmed Shaikh, Abdullah Ayub Khan, Asif Ali Laghari (2021)

[10]. Multi-features extraction based on deep learning for skin lesion classification. SamiaBenyahia, BoudjelalMeftah, Olivier L´ezoray (2021)

[11]. https://www.wcrf.org/cancer-trends/skin-cancer- statistics/#:~:text=skin%20cancer%20data ,Melanoma%20of%20skin%20is%20the%2017th%20most%20common%20 cancer%20worldwide,the%20reporting%20of%20cancer%20statistics.

[12]. https://www.scienceabc.com/eyeopeners/why-does-the-thickness-of- skin-vary- over-different-parts-of-the-body.html

[13]. https://www.who.int/news-room/fact-sheets/detail/cancer

[14]. https://www.ncbi.nlm.nih.gov/books/NBK441949/

[15]. https://www.mayoclinic.org/diseases-conditions/skin-cancer/symptoms- causes/syc-20377605
[16]. Skin lesion classification using ensembles of multi-resolution EfficientNets with metadata Nils Gesserta,b,∗ , Maximilian Nielsenb,c , Mohsin Shaikhb,c , René Werner b,c, Alexander Schlaefer (2020)
[17]. Skin Cancer Detection: A Review Using Deep Learning Techniques
Mehwish Dildar, Shumaila Akram, Muhammad Irfan, Hikmat Ullah Khan, Muhammad Ramzan, Abdur Rehman Mahmood, Soliman Ayed Alsaiari, Abdul Hakeem M Saeed,
Mohammed Olaythah Alraddadi, and Mater Hussen Mahnashi
[18]. Deep learning design for benign and malignant classification of skin lesions: a new approach
Wessam M. Salamaa ,Moustafa H. Aly
[19]. M. E. Celebi et al., A methodological approach to the classification of dermoscopy images, Comput. Med. Imaging Graph., 2007,
DOI: 10.1016/j.compmedimag.2007.01.003.
[20]. Application of an artificial neural network in epiluminescence microscopy pattern analysis of pigmented skin lesions: a pilot study,
M. BINDER, A. STEINER, M. SCHWARZ, S. KNOLLMAYER, K. WOLFF, and H. PEHAMBERGER, Br. J. Dermatol., 1994, doi: 10.1111/j.1365- 2133.1994.tb03378.x. [21]. H. Dermatoscopy of pigmented Bowen's disease. J Am Acad Dermatol 62, 597– 604 (2010). Cameron, A., Rosendahl, C., Tschandl, P., Riedl, E. & Kittler