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COMPARATIVE STUDY OF AUTOMATED TECHNIQUES FOR MULTILABEL SKIN CANCER CLASSIFICATION

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Abstract. The issue of skin cancer is among the most widespread and dangerous diseases due to the fact that people are not aware of its symptoms and the preventive measures. It is number four in the list of most burdening diseases in the world and the mortality rate has become more alarming. It is important to ensure that cancer is stopped at an early stage. In this paper, multi-label skin cancer is identified and categorized and the most optimal methods applied based on machine learning and image processing. Preprocessing techniques are utilized to eliminate the irrelevant and unnecessary attributes on the label encoder, and conventional features are applied to yield standard features of the functionality through the scale of input variance unit. Also, different machine learning methods were experimented to check the performance of all classifiers on HAM10000- metadata dataset. The experimental analysis was performed on the HAM10000_metadata dataset that has seven types of skin cancer. The findings show that SVM, DT and GNB machine learning algorithms recorded the most accuracy compared to the other classifiers.

Keywords: Skin Cancer, Machine Learning, Deep Learning, CNN, ResNet, DenseNet, Multi-Label Classification, Medical Image

I.INTRODUCTION

Another disease that is prevalent in many countries is skin cancer. It happens in human beings, animals, and plants, but it is least common among the others. The increasing incidences of skin cancers are a major issue of concern in the world and cause severe burden. The fourth greatest cause of mortality in the world is skin cancer. It can target individuals of any age, yet mostly of children and the elderly [1]. Early detection and treatment of the disease would involve surgery [2]. The unpredictable type of skin cancer is melanoma. It influences the skin cells, hair and mucous membranes. Skin cancer may occur almost in any damaged skin cell. It is very much possible to occur in almost everyone and occurs as the cells of the skin get mutated into cancerous (malignant) cells. Radiation by the sun, especially the UV radiations, leads to skin cancer [3].

Skin cancer affects many individuals across the world, without the knowledge of the people. The cancer of the skin is caused by intense ultraviolet (UV) rays of the sun. UV radiation is one of the radiations that move through our atmosphere to reach the earth. It is capable of appearing on any part of the body and it has many different variants. Even though it cannot be prevented, you can mitigate your chances of getting skin cancer. The skin cancer is a weighty concern and it can be quite hazardous [4]. One should also be cautious of risks and take measures in order to save oneself against the harmful radiation. Skin cancer occurs in the United States when the skin cells begin to grow anomalously and in an excessive speed.

II.LITERATURE REVIEW

Other scientific investigations tried to enhance the chances to detect and classify skin cancer in the initial stage with the help of traditional image processing, machine learning, and deep learning. Codella et al. [1] launched the International Skin Imaging Collaboration (ISIC) challenge that offered a uniform dataset and assessment scheme to automated analysis of skin lesions. It enabled the justifiable comparison of various algorithms and contributed to the development of the research in melanoma detection significantly. Esteva et al. [2] indicated that deep convolutional neural networks are able to provide similar showing to dermatologists when trained on large data sets of dermoscopic images indicating that these models are also able to reach high diagnostic accuracy similar to that of medical professionals. Shanthini et al. [3] have provided an extensive list of deep learning methods in skin lesion classification. They have summarized some of the CNN based and transfer learning approaches and pointed out their efficiency and limitations, including data dependency and immense computing requirements. The optimized convolutional neural network with decision-making techniques proposed by Saleh et al. [4] to enhance the accuracy of classification was complex in nature; however, more complex systems yielded better results.

On the same note, Barata et al. [5] came up with SkinLesNet, a novel multi-layer deep convolutional architecture. This enhanced melanoma detection performance, yet required significant amounts of training resources.Recent research has worked on enhancing the process of feature representation and efficiency of networks. Liu et al. [6] refined the categorization of lesions by including ResNet-50 with adaptive spatial feature fusion to enable it to better extract multi-scale features and be robust. Residual learning, the initial idea proposed by He et al. [7], not only solved the vanishing gradient issue, but also the training of very deep neural networks became possible. It has become an influential architecture upon numerous medical image classification tasks. Also, by adding dense connections between the layers to each other, Fawcett [9] emphasized the necessity of the ROC analysis and such measures of performance as accuracy, recall, and AUC to estimate the model reliably. A large, publically available repository of dermoscopic images, which is used to support the creation and test of automated diagnostic systems, is also found in the ISIC archive [10]. All these studies demonstrate that the approaches based on deep learning prove much more effective than the conventional methods when it comes to the classification of skin lesions. Nevertheless, such complexities as the imbalance of classes, computation costs and real-time applicability remain. This is to encourage the proposed system to aim at an effective preprocessing, model comparison, and strong multi-label classification to improve the diagnostic performance.

III.EXISTING METHODODLGY

On top of automated and intelligent diagnostic systems, the existing system of screening skin cancer is primarily based on manual or semi-automatic procedures performed by dermatologists. This is a conventional method where dermoscopic or clinical photographs of skin lesions are taken after which visual assessment is done according to clinical features such as asymmetry, change in border, color change, diameter, and the texture of the lesions. The diagnosis mostly relies on knowledge and individual prejudice of medical practitioners. One of the great disadvantages of this type of manual examination is the fact that it is time-consuming, very labor-intensive, and highly dependent on human experience. Also, various types of dermatologists might view the same lesion differently, which leads to inter-observer variability and unreliable diagnostic outcomes.Another relevant problem with the conventional diagnostic systems is the absence of automated feature extractors and smart tools of classification. In ambiguous cases, biopsy, histopathological tests or even lab tests have to be done, which increases expenses and time of diagnosis. The invasive procedures also may be uncomfortable to patients. Also, manual systems cannot handle the medical images generated in healthcare facilities in large volumes as they are currently and could not support large-scale screening initiatives due to their lack of flexibility, scalability, and the learning algorithm (they are not based on machine learning or deep learning algorithms). In the absence of intelligent models, it is unable to learn using previous data set and enhance the quality of the diagnostic result through experience.

This weakness impacts on its capacity to adequately identify complicated lesions or those at an early stage and leads to a higher risk of misdiagnosis or delay in detection. Moreover, the classical-style has never offered real-time predictions, automated multi-label classification or high through put processing; essential to contemporary clinical implementation. These weaknesses suggest that the present-day diagnostic methods have a set of issues related to the efficiency, consistency, and scalability.This heralds the necessity of a smart, automated, and data-driven solution that might provide detecting skin cancer faster, more accurately, and reliably.

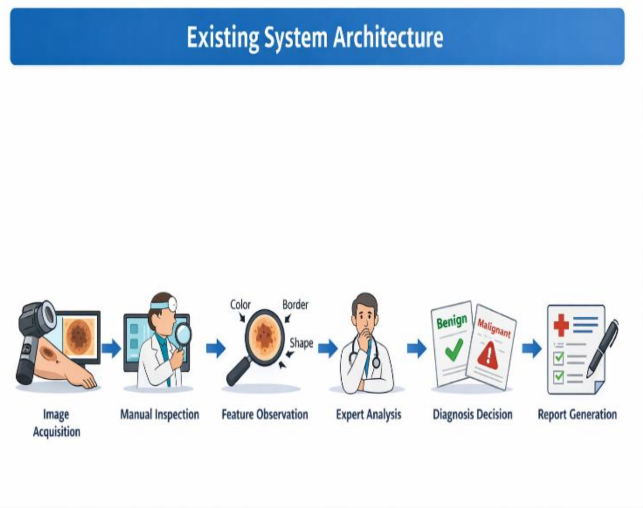

Fig. 1. Architecture of the Existing System

IV. PROPOSED METHODODLGY

The suggested framework will enable the detection of skin cancer effectively due to the automated extraction and analysis of important features of the dermoscopic images. This will ease the burden on manual inspection of dermatologists. This system is capable of integrating both structural and statistical features of lesions, which are color change, texture, shape, and border abnormality to help in the accurate diagnosis of the disease. Data pre-processing methods, including resizing, normality, removing noise and data augmentation measure up to enhance accurate images, reduce bias, and augment model uses. A variety of supervised learning classifiers such as Support Vector Machine, Random Forest, Convolutional Neural Networks, ResNet, and DenseNet are applied to be able to define various boundaries of the decision and evaluate the classification results. Ensemble and deep learning architectures make the predictor more resistant to overfitting and they enable automatic hierarchical feature learning. Also, a multi-label classification strategy will allow identifying multiple skin conditions simultaneously. Generally, the framework provides scalable, flexible and highly accurate in diagnosing skin cancer reliably and real time with auto diagnosis.

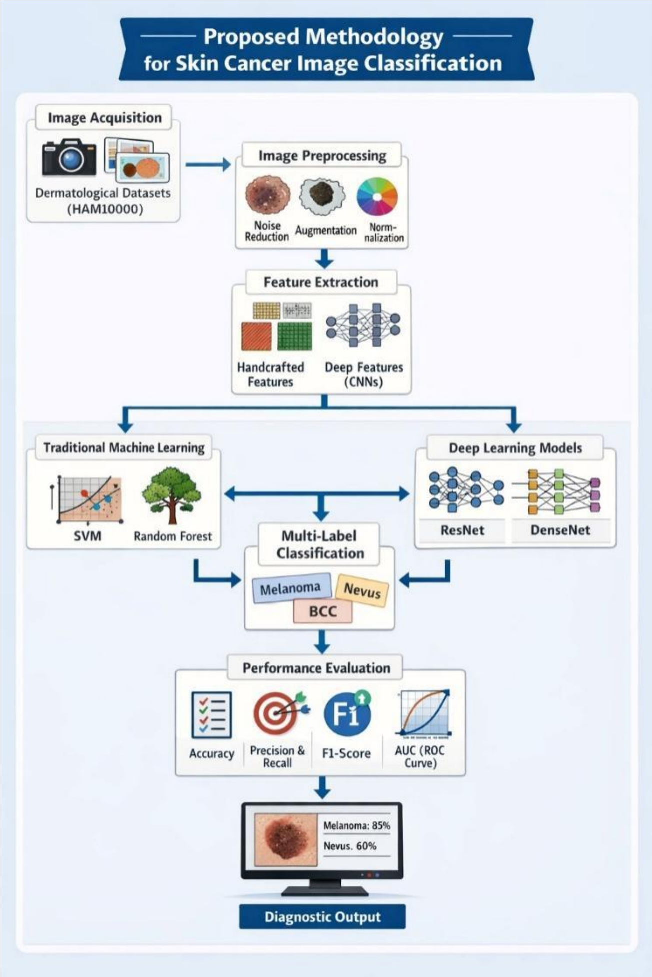

Fig. 2. Architecture of the Proposed skin cancer classification

A. Image Acquisition

The data on dermoscopic images in this research is provided by real and publicly available medical repositories such as the International Skin Imaging Collaboration (ISIC) database and the HAM10000 data. The samples collected are clinical verified and marked by highly qualified dermatologists. These data sets have a huge collection of skin lesion pictures that reflect benign and malignant lesions (melanoma, basal cell carcinoma, nevi, and others pigmented lesions). The labelling and standardization of images provide a stable supervised learning process that can be used on classification tasks. There are ground-truth labels on each image, making the proposed models be able to train and be tested reliably. The system is also more capable of generalizing and is robust with the use of large amount of real clinical data that can have the benefit of managing a wide range of types of skin lesions in the real world setting of diagnosis.

B. Image Preprocessing

This stage involves preprocessing so as to enhance the quality, consistency and reliability of the dermoscopic images obtained before it is deployed on the learning models. Raw images are characterized by noise, artifacts on the hair, uneven lighting, scale and contrast differences. These problems may be detrimental to classification. In order to correct this, we scale the images to equal sizes, equalize pixel values, boost contrast and remove noise. Data augmentation methods such as rotation, flipping, zooming, and cropping are also used in order to artificially expand the dataset and address the problem of class imbalance. These preprocessing steps stabilize the process of learning, decreases bias and significantly enhances the strength and generalization of the system.

C. Feature Extraction

Another essential procedure is a feature extraction that will assist in distinguishing the essential features that mark the difference between the types of skin lesions. At this step, significant visual characteristics, including color-distribution, texture, lesion boundaries, asymmetry, and irregularities of the shape, are collected as handcrafted characteristics. These clinical manifestations are famous to confront malignant behavior diagnosis. Also, deep learning tools automatically find hierarchical high-level features in convolutional layers which extract complex spatial and contextual information. By converting image data into numerical representation of features, computationally efficient processing can be conducted and better differentiation of the classification models achieved.

D. .Model Prediction and Training.

At this step, machine learning and deep learning models are trained under the supervision of the extracted features and processed dermoscopic images. The data is subdivided into training, validation and testing sets in order to provide reliable results in evaluation and generalization. Other traditional machine learning classifiers include Support Vector Machine (SVM) and Random Forest (RF) which are used to provide the baseline models. SVM builds the best decision boundaries whereas, Random Forest is more stable since it is an ensemble learner and less prone to overfitting. Deep learning models such as Convolutional Neural Networks (CNN), ResNet, and DenseNet are applied to learn automatically the hierarchical image features of an image to enhance the accuracy. Transfer learning assists in fine-tuning pre-trained networks, which decreases the training time and improves performance. In prediction, the trained models provide probability scores of every lesion category. The model produced the best results is selected on the basis of such metrics as accuracy, precision, recall and F1-score. In practice, one skin lesion can be demonstrating the characteristics of several disease groups. Thus, rather than the single-label system, the proposed system uses a multi-labeling one. Instead of providing only one label, the model provides multiple possible labels and probabilities associated with the labels. This technique enhances the diagnostic flexibility and is more representative of clinical practice and gives the opportunity to identify diseases more completely.

V. DATA SET DISCUSSION

The dataset used in the proposed system is the HAM10000 (Human Against Machine with 10,000 training images). It is a public dataset that is commonly used in automated skin lesion analysis. It is comprised of 10,015 dermoscopic images that have been collected in different populaces and clinical sources. This series provides a representative and a wide variety of pigmented skin lesions. All images come annotated and confirmed by trained dermatologists which gives high quality labels to any supervised learning task.The HAM10000 dataset consists of seven major classes of skin lesions: Melanoma (mel), Melanocytic Nevi (nv), Basal Cell Carcinoma (bcc), Actinic Kirketosis (akiec), Benign Keratosis-like Lesions (bkl), Dermatofibroma (df), and Vascular Lesions (vasc). The set of these classes comprises malignant and benign conditions, which proves to be adequate to clinical diagnosis in the real world. However, the dataset has class imbalance. Some categories, like melanocytic nevi, have significantly more samples than rarer classes, such as dermatofibroma and vascular lesions.

Fig. 3. Dataset

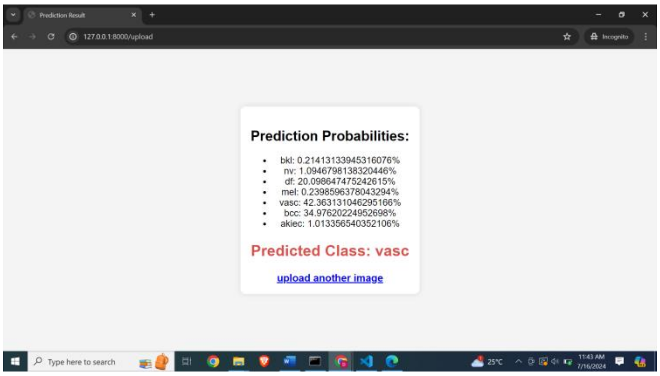

Fig. 5. Prediction Phase Output

VI. RESULTS JUSTIFICATIONS

The proposed system was experimentally analyzed regarding the possibility of detecting various types of skin cancer based on the usage of the machine learning and deep learning procedure.

Figure 4 is a prediction form that will be the user interface of the proposed skin cancer classification system. It enables users to share images in dermoscopic images and get a set of automatic diagnoses. This is a platform that is interactive and easy to use. An image of a skin lesion could be sent by dermatologists or users to analyze it. The form is compatible and convenient as it supports standard image formats, such as JPG, PNG, and JPEG. Once an end user chooses and uploads an image, it is transmitted to the backend system that does the preprocessing and classification of the image.

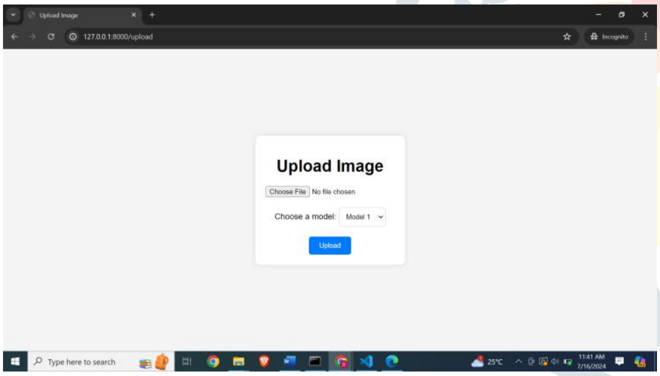

Fig. 4. Prediction Form

The outcome of the prediction stage of the proposed system is depicted in figure 5 above and represented the final classification results obtained by the skin cancer detection system following inspection of a dermoscopic image. The model generates a probability score of all categories of skin lesions included in the study, on each input image. They include Melanoma (mel), Melanocytic Nevi (nv), Basal Cell Carcinoma (bcc), Actinic Keratosis (akiec), Benign Keratosis-like Lesions (bkl), Dermatofibroma (df) and Vascular Lesions (vasc). The values of the probabilities indicate the level of confidence that the model has to classify the image into any of the disease classes.
The system then finds the overall foreseen category by searching the highest probability score. This is a process that guarantees sound decision-making.

VII. CONCLUSION

The method described in this paper involves the application of machine learning and deep learning in automatic multi-label classification of skin cancer on the basis of the dermoscopic images. The model focuses on the extraction and analysis of significant visual cues such as color, texture, shape, and border abnormality. This method takes less time to perform a manual clinical examination and enables to identify the skin lesions in a short period. Lesions are further separated into different disease categories using a number of supervised learning models. Some of these models are Support Vector Machine,Random Forest, Convolutional Neural Networks, ResNet, and DenseNet. The findings indicate that deep learning algorithms are more effective in identifying a complex pattern on the image and enhance the process of diagnosing better. Transfer learning enhances the performance and reduces the time spent in training and decreases the quantity of data required. The multi-label framework proposed has the capability of detecting several skin conditions simultaneously, and thus can be applicable in a clinical setting. The system in its entirety provides scalable, fast and reliable decision-supporting solutions. It can also be advanced whereby more features or advanced learning models can be added to advance the performance of detection.

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