Skin Cancer Identification using Deep Learning Model on the HAM10000 Dataset

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ABSTRACT

Skin cancer, being a worldwide health problem, creates major physical, mental and emotional stress. Traditional physical finding is majorly time-taking and subjective, depending on much upon dermatologists' knowledge. In our work, an extensive skin cancer disease analysis is proposed for ease in diagnosis by using deep learning models. The HAM10000 dataset is the standard for estimating skin cancer disease by AI detection approaches. It consists of more than 10,015 dermoscopic images labeled with seven different diagnostic categories. We have identified the skin cancer ResNet18 to the HAM10000 dataset. The procedures in detail, experimental setup, results, and conclusions include reviewing findings and potential consequences on the clinical procedure.

Keywords: skin cancer, CNN, ResNet, HAM100000 Dataset.

I. INTRODUCTION

Skin cancer is one of the common and conceivable very critical and life-threatening that basically needs very early diagnosis and prompt intervention and wide spreading varieties of cancer globally, with millions of new patients identified each year. Accurate recognition has a lot of challenges, and it often requires extensive manual examination by medical professionals/doctors. Skin diseases are one of the most highly contagious diseases worldwide. It is right to say that dermatological illnesses are supremely contagious. In 2018, the World Health Organization (WHO) approximated by its study that skin cancer caused the deaths of approximately 2794 individuals in Bangladesh [1]. Furthermore, the World Health Organization (WHO) [2] also stated that a staggering 9.6 million individuals have lost their lives globally in 2018, with over 14 million cases being officially identified as dermatologious illness [3]

It points to a change in skin color or texture. Skin diseases may result from some, bacterial, fungal, allergic reactions or viral infections. Dermatologists used to depend on experience and physical examination of the skin lesions (biopsy) for perfect diagnosis of these diseases. These procedure, however, are time-taking and there is chance of human error. Machine learning overcomes these problems through algorithmic and data-driven processing [2].

ML (Machine learning) has transformed the detection of skin disease [2] by recognizing it in its early stages, cutting down the work of dermatologists, and hypothetically reducing healthcare expenses. Convolutional Neural Networks

(CNNs) [4], a widely used deep learning method, are basically utilized for recognizing and classifying skin abnormalities from high-definition images. After being trained on massive sets of data, the models become capable of competing with the performance of dermatologists, thus enhancing the accuracy and rapidity in diagnosing skin disease. This method improves the effectiveness of investigation, decreases diagnostic misadventures, and is quite efficiently used in rural or limited-resource areas.

The aim this paper carries is to diagnose and detect skin problems based on the observation of lesion pictures. The system will give a degree of usability, being made available in each AI model, and have the capacity to analyze different forms of skin images. It is designed to diagnose and classify numerous forms of skin cancer accurately and effectively based on Dermatological images. The focus of this study is automated skin disease prediction from the HAM10000 dataset [4], which comprises 10,015 dermatoscopic images distributed among seven classes. High class imbalance of the data set is one of the main challenges since it renders predictions a challenging feat based on varying numbers of observations per class. Aims for earlier identification and discovery of skin disease and, accordingly, improvement in the treatment of patients and facilitation of assessment of dermatological illnesses.

II. TYPE OF SKIN CANCER

There are several types of skin cancer. Here we introduce some of the most important ones, providing some medical information according to Kousis et al. (2022) [5].

A. *Melanoma (MEL)*

The extremely serious type of skin cancer, it is formed when unrepairable DNA Destruction in skin cells results in gene mutations that make the skin cells expend rapidly and become malignant skin cancer. The reason behind this situation is typically Ultraviolet radiation exposure (UV) light or tanning beds. In case it is metastasized to the lymph nodes or internal body

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organs, it is 38% and 86% lethal, respectively. But if it is detected early and treated, the infant mortality is only 0.2% within the upcoming next 5 years. The challenge in detection is that melanoma, in initial stages, resembles other benign skin lesions, and yet it tends to occur because of them.

B. Basal Cell Carcinoma (BCC)

According to Kousis et al. (2022) [5], it is the most prevalent kind of cancer. The basal cells that are embedded in the hidden layers of the cutaneous surface, or superficial skin layer, are where this cancer develops. Almost majority of these cancers appear on different parts of body that receive a lot of sun exposure or contact, such as ears, face, neck, head, back and shoulders. But occasionally, cancers can also form on parts of the body that are not exposed to sunlight. In addition, exposure to arsenic, radiation exposure, chronic inflammation of the skin and burn complications, scars, various infections, different vaccines or even body ink tattoos are aggravating factors for causing skin cancers.

C. Actinic Keratosis and Intraepithelial Carcinoma (AKIEC)

According to Kousis et al. (2022) [5], an estimated 450,000 new occurrences of squamous cell carcinoma (SCC), the primary skin cancer category of AKIEC, are detected every year. This type of cancer is the second most prevalent skin cancer (after BCC) and occurs in the acanthoses, which form the outer layer of the skin. SCC may develop in anywhere location on the skin, involving the oral self-lubricating membranes and genital mucous membranes. Naturally enough, it occurs most frequently in those locations on the human body which are subjected to sun exposure, such as the ears, face, and lower lip, hairless area of a head bone, neck, hands, arms, and legs. In most instances, skin at individuals' sites looks as if sun harm has resulted in screw up, color transforms and loss of resistance.

D. Dermatofibroma (DF)

Dermatofibroma, abbreviated as DF, is a benign fibrous lesion on the skin, which is essentially a product of benign growth of fibroblasts and associated tissue cells. The cause of a dermatofibroma is usually minor skin trauma, such as an insect bite, minor shave cuts, or an ingrown hair. The cause, however, is not always clear. Dermatofibromas [4] are benign growths that are self-limited, meaning they are not likely to metastasize or become malignant.

E. Melanocytic nevus (NV)

The point of reference is a nevus, it is where melanocytes in different skin layers are pigmented. They manifest during the human embryonic stage, in children and adolescents, and occasionally in adults and older people. A black or brown smooth patch, epidermal nervousness is rarely prone to growth and cancer.

F. Benign Keratosis Lesions (BKL)

According to Kousis et al. (2022) [5], It is the most widespread type of benign cancer and occurs in middle-aged and elderly peoples identical to a form of seborrheic hyperkeratosis. Seborrheic hyperkeratosis is a condition that occurs due to the deposition of keratin in the stratum corneum. It has also been reported to appear rapidly and to resemble skin cancer.

G. Vascular lesion (VASC)

The cause of vascular lesions on the skin is the dilation of a small number of blood vessels on the skin. The lesions are normally developed on the feet or face. The lesions are not harmful but can reason excruciating stinging on the legs after long periods. At times, they are associated with serious venous diseases.

Dermatofibroma (DF): This is a normal benign fibrotic lesion. The cause is a benign growth of cells on the skin. The lesion is normally a discrete oval or round, brown or yellowish, 0.5- to 1-cm-diameter nodule.

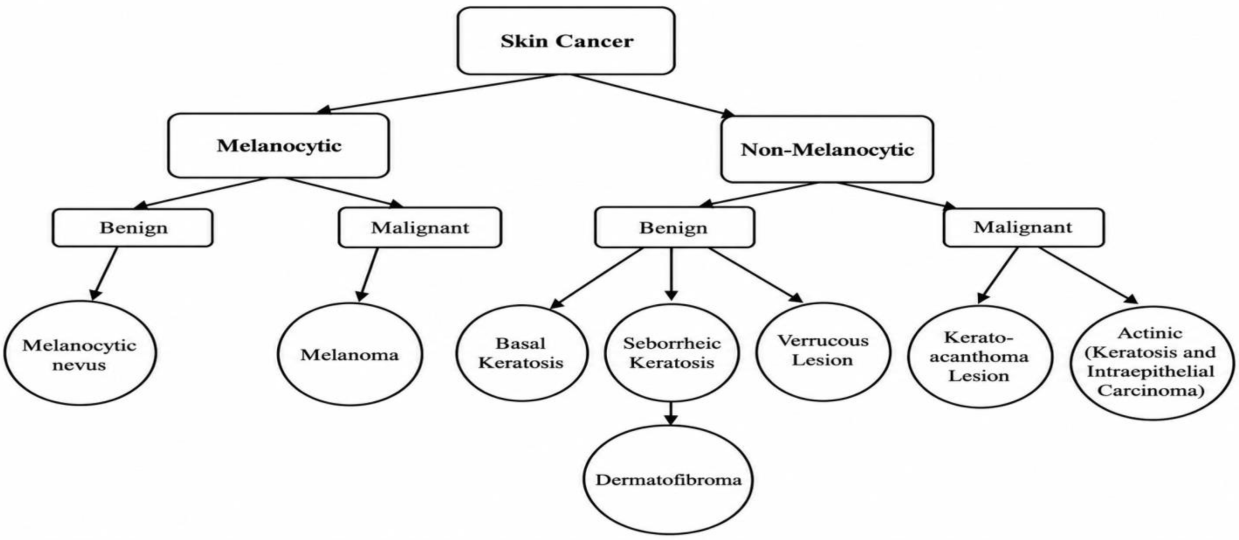

Fig 1: Type of Skin Cancer

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III. LITERATURE REVIEW

Natha et al. (2024) [6] applied data augmentation to increase training diversity and tested Decision Trees, Naive Bayes, and Neural Networks, with the latter achieving the highest accuracy. Their research showed the potential of Neural Networks, which was further enhanced through data augmentation, in reducing the need to use invasive procedures that can be highly useful in early skin cancer detection. Gouda et al. (2022) [7] also developed a CNN architecture with noise reduction techniques [6], which calculated high accuracy and robustness in detecting various skin cancer types, outperforming the various traditional methods and offering a cost-effective solution for easy diagnosis.

Monika et al. (2020) used publicly available datasets and Principal Component Analysis (PCA) for feature selection [8]. By utilizing trained models such as Logistic Regression, SVM, and Decision Trees, with SVM producing the best results. PCA was useful in reducing overfitting, thus improving the models' accuracy calculation. Esteva et al. (2017) took deep learning as a step further, using CNNs for classification and achieved dermatologist-level accuracy [9], while Tschandl et al. (2019) and Brinker et al. (2019) substantiated these findings, showing that machine learning models could either match or surpass human experts in skin cancer classification [10], making it more efficient.

In the field of automated detection, Han et al. (2018) and Haenssle et al. (2018) both presented that deep learning models (specifically CNNs) [11] performs equivalently or better than dermatologists in recognizing conditions like melanoma. Nasr-Esfahani et al. (2019) [12] also presented the efficiency of machine learning algorithms to section and categorize skin lesions easily. Other researchers, such as:

Menegola et al. (2018) [13] and Du et al. (2018) provided comprehensive assessments of machine learning (ML) methods and intelligent systems which helped in recognizing both their strengths and weaknesses in diagnosing melanoma. Further advancements include Codella et al.'s (2019) who analyzed deep learning's ability to classify skin lesions and showcased improvements in detection capabilities [14], and Sonavane et al.'s (2020) deep learning framework exhibited promising results for clinical applications [15]. Yu et al. In 2018, performed a review collective deep learning and fuzzy SVM to absolute the consistency of melanoma identification. In addition used classified deep learning networks to excellent diagnostic accuracy. Feature extraction procedures such as those utilized by Barata et al. (2023) [16] which included joint color features and texture also substantially enhanced the accurateness of melanoma recognition. Finally, Demyanov et al. (2019) used visible and thermal images in deep learning models that led to better results in identifying skin cancer [17] .In contrast, the last few years have seen a growing interest in using hybrid deep learning methods to predict and diagnose skin cancer. This is because these methods are new and help in expanding the possibilities of medical image analysis. Maniraj and Maran (2022) [18] introduced a hybrid model that incorporated 3D wavelets and sub-band fusion to improve skin cancer diagnosis and succeed in achieving notable enhancements in classification accuracy through the application of deep learning techniques. Ashraf et al (2020) [19] employed a region-of-interest-based transfer learning framework thereby illustrating the capacity of deep neural networks to extract crucial features from dermoscopic images which in turn facilitated the early detection of skin cancer. Furthermore, Byrd et al. (2018) [20] emphasized the importance of understanding the human skin microbiome that may influence skin cancer progression and the development of diagnostic models. Elgamal's (2013) study clearly demonstrated the use of automatic classification techniques for images of skin cancer. This is a predecessor to modern deep learning methods. Statistical reports by various organizations, such as the American Cancer Society (2021) highlighting the increase in the prevalence of melanoma which is occurring generally so easily to anyone. This has to be addressed using modern techniques to prevent an increasing incidence [21]. Khan et al. (2019) also contributed by enhancing melanoma and nevus categorization through digital imaging which plays crucial role in precise identification [22]. The literature assessment indicates that the most common models used in this work are deep learning and hybrid used methods and have fairly reached a high degree of accuracy ranging from 77% to 87%.

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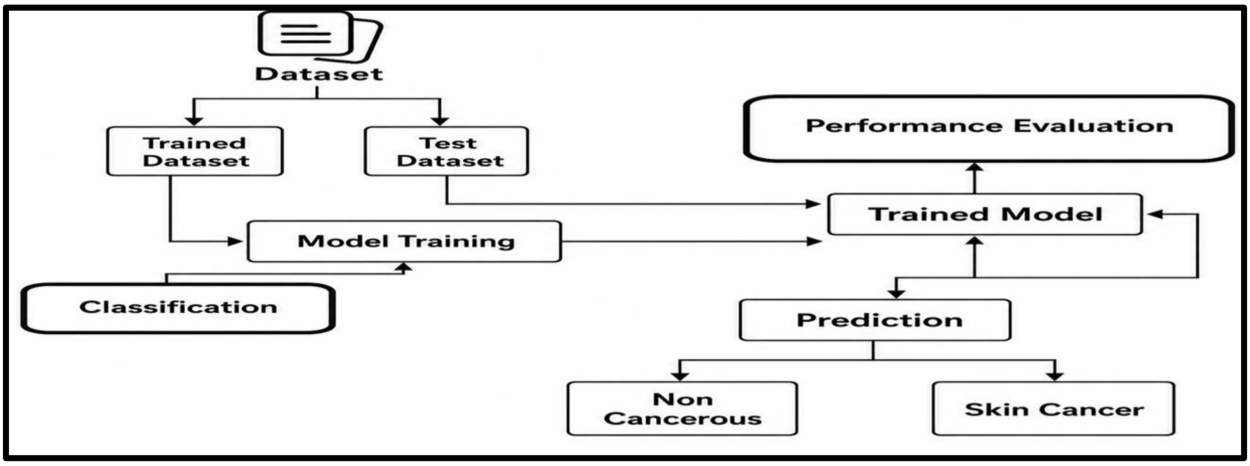

Fig 2: Process for skin cancer detection and classification

IV. PROPOSED ENERGY-AWARE PRIORITY SCHEDULING FRAMEWORK

The performance of Convolutional Neural Networks becomes especially impressive when combined with transfer learning and hybrid approaches that too particularly in tasks like feature extraction and disease classification. However, there are numerous challenges to be faced in the process, and these include: The need for large and well-annotated data sets necessitates computationally intensive processes; there are also interpretability issues. The models. Despite these challenges, there is great promise in data expansion and multi-level architecture. Exhibiting great potential in expanding recognition generalizability and accuracy. Skin cancer detection is one area that needs much study to come up with improved diagnosis and treatment outcomes, reduced healthcare [23] expenses, address the shortage of dermatology specialists, and handle large volumes of clinical imaging data, improve investigative correctness, apply scientific advances, and enable telemedicine. All factors work together to increase efficiency, accessibility, and effectiveness in healthcare to detect skin cancer.

V. DATASET

The performance of Convolutional Neural Networks becomes especially impressive when combined with transfer learning and hybrid approaches that too particularly in tasks like feature extraction and disease classification. However, there are numerous challenges to be faced in the process, and these include: The need for large and well-annotated data sets necessitates computationally intensive processes; there are also interpretability issues. The models. Despite these challenges, there is great promise in data expansion and multi-level architecture. Exhibiting great potential in expanding recognition generalizability and accuracy. Skin cancer detection is one area that needs much study to come up with improved diagnosis and treatment outcomes, reduced healthcare [23] expenses, address the shortage of dermatology specialists, and handle large volumes of clinical imaging data, improve investigative correctness, apply scientific advances, and enable telemedicine. All factors work together to increase efficiency, accessibility, and effectiveness in healthcare to detect skin cancer.

VI. OVERVIEW OF MODELS

CNN - It is a strong implement in deep learning technology, which is used in the detection of an object, the classification of the object, and the recognition of the image. The architecture of CNN is based on or represents the graphical cerebral cortex of the brain. CNN has layers called convolutional layers, which procedure the input images by scanning the input image through a set of filters called grains to find identifiable features like textures, edges or patterns. To help the network understand intricate linkages and patterns, the activation function, ReLU, is applied elementwise to the data to introduce non-linearity. The pooling layers reserve critical information while decreasing the feature maps' dimensions. The fully connected layers are connected to each other to make a classification. It has an output layer with a SoftMax activation function that provides the likelihood of each class in a multi-class and classification problem. Different architectures often include dropout layers to prevent overfitting and improve generalization on new data. The output layer will make use of learned features to make the final prediction, using one neuron (using)with a sigmoid activation function for preparing binary data classification and SoftMax activation function is used in the case of multi-class categorization.

ResNet: A deep learning of architecture mainly adopted for image classification tasks [24]. The introduction of skip connections allows it to go much deeper without suffering from the vanishing gradient problem. The gradients can flow uninterrupted thus allowing the training of very deep models. It is constructed using residual blocks as their primary architectural units. Every block typically incorporates two or more convolutional layers along with crosscut connections

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that allow the direct flow of data across layers. This design prevents the dreadful circumstances often encountered in extremely deep neural networks. ResNet architectures are accessible in multiple arrangements with variable depths, generally denoted as ResNet-X where X suggests the number of layers in the network. While growing the depth of the model, it can improve feature acquiring and overall performing and also improves the computational sources necessary during training. ResNet has succeeded strongly in performing across various image classification benchmarks and has been expansively executed in both practical and research efforts. Its efficiency is largely attributed to its ability to learn complex visual representations, maintain training stability in deep architectures, and reduce the risk of overfitting.

VII. RESULTS AND DISCUSSIONS

The analysis of the results can be divided into two parts: first, the review of pretreatment results and description of the performance experimental setup; second, the thorough evaluation to show the outcomes of three models.

A. Experimental set-up

Specifically, the train to test ratio for ResNet models is maintained at 80:20. Table1 lists the models' parameters.

The model's variable parameters are noteworthy. In particular, ResNet has a significantly greater number of layers. Additionally, ResNet extracts more characteristics than other models.

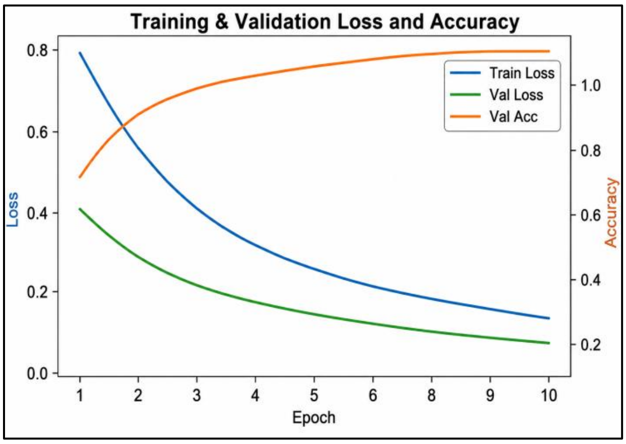
TABLE 1
EXPERIMENTAL PARAMETERS SETUP FOR RESNET18 MODEL

Parameters	ResNet18
No. of Class	7
No. of Convolution Layers	20
No. of Dense Layers	1
No. of Epochs	10
Batch size	32
Pooling Function	MaxPooling2D
Filtering Function	Conv2D
No. of features extracted	512
Train Accuracy	0.85

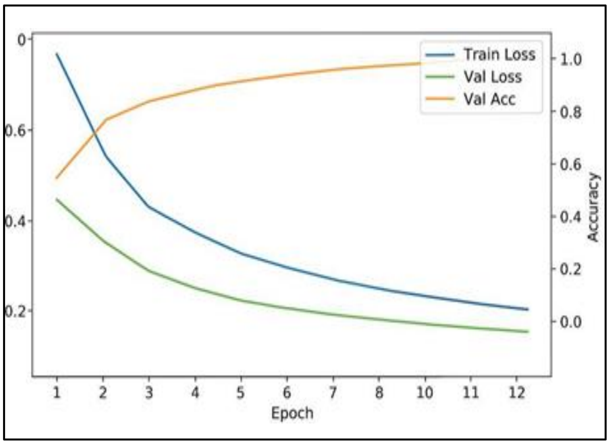
The number of interpretations per class is shown in Figure 3. Note: There are seven classes,0-6. It can be observed that these classes cover more than 8012 images out of 10015 images.

B. Performance Evaluation

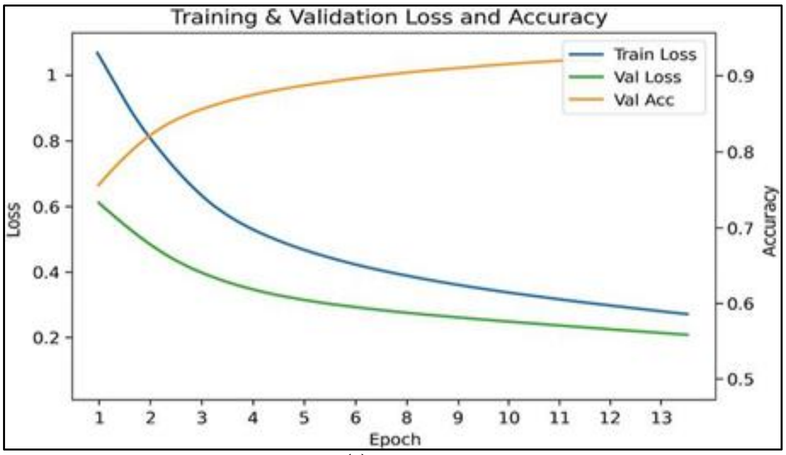
We have run the skin cancer diagnosis test multiple times as per Epochs, batch size etc. Figure 3 showing the accuracy for running multiple tests. We got 85% accuracy to detect skin cancer.



(a)



(b)



(c)

Fig 3: (a), (b), (c) Accuracy for ResNet 18 for HAM1000

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VIII. CONCLUSION

This study has determined on the usage of enhanced deep learning categorization intended for the automation of skin cancer diagnosis, such as ResNet. The demonstration is brought out by investigating the HAM10000 dataset. Conclusions have drawn a focus on the utilization of automated diagnosis to address the global health burden brought about by skin disorders through the delivery of better accuracy efficiently. Diagnosing skin cancer from clinical images/clicked images is very difficult due to multiple aspects including distinctions in image quality of the cameras present and various other conditions, although these deep learning models demonstrated promising abilities. Skin disease classification witnessed significant developments in studies, though around is further room for advancement. The programmed segmentation process implemented in the study at period fails in the correct identification of skin lesions, hence the requirement for more robust segmentation strategies. Segmentation techniques should be further improved, the development of real-time systems for skin disease detection should be worked on, deep learning approaches should be implemented, object detection systems integrated, and the practical implementation of the model tested clinically. This sophisticated technology can be implemented in collaboration with medical professionals to include in routine dermatological examinations for simple and easy identification.

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