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DEEP LEARNING-DRIVEN SKIN DISEASE DIAGNOSIS: ADVANCING PRECISION AND PATIENT-CENTERED CARE

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Abstract. Skin diseases are in the middle of the most prevalent conditions, arising from a myriad of factors including viral infections, bacteria, allergies, and fungal pathogens. Appropriate detection of these conditions is essential for effective treatment and management. Further, Deep learning methods are employed to enable early-stage detection, with a particular emphasis on the pivotal role of feature extraction in the classification process. This research emphasizes the significance of a patient-centered approach, aiming to provide responsible and effective solutions for skin diagnoses. In pursuing more accurate and timely skin condition diagnoses, we turn to deep learning techniques, leveraging the HAM10000 dataset. Initially, we perform different prepossessing techniques on selected datasets to handle class imbalance and a Convolutional Neural Network and fine-tune hyper-parameters such as with or without Dropout, CW, FL, and Using Global Average Pooling. Our technique excels in distinguishing diverse skin, Gender, localization, and Cell types with reliable evaluation metrics such as precision, recall, FI Score, and specificity. Our technique not only subsidizes the healthcare field but also underscores the potential of advanced technologies in enhancing early skin disease detection and medical decision-making.

Key words: Deep Learning, Neural Networks, Skin Lesions Classifications

1. Introduction. Skin syndromes are more common than other viruses. Skin conditions can be transported by viruses, microbes, allergies, mycological infections, etc. Skin lesions are viruses caused by many factors such as poison, sensitivities, cell growth, etc [1]. They usually appear through outward abnormalities on the skin, such as discoloration, growth abnormalities, and tissue changes. Eczema [2], psoriasis [3], acne, moles, and fungal infections are among the most chronic dermatological conditions everywhere in the world. Cities, towns, and countries have different forms of skin illnesses. Certain factors, such as heredity, dietary and socioeconomic position, profession, personal habits, and civilization, affect the pattern and frequency of presentation of certain skin diseases. Skin conditions make up a large portion of all ill, towns, and illnesses that doctors treat since they are widespread in the overall population [4]. Some skin conditions have no indications for months, which causes the medical condition to grow and feast. A dermatologist may intermittently have trouble diagnosing a skin condition because treatment options that are inappropriate for the condition could have negative effects.

Further, the image-processing approach has quick and advanced diagnoses of skin diseases and medicines over the past few years. Magnetic resonance imaging (MRI) [5], Digital subtraction angiography (DSA), and Computed tomography (CT) [6] are a few instances of imaging equipment with a broad spectrum of potential uses in everyday life for individuals. HAM10000 ("Human Against Machine with 10000 training images") dataset is a large group of multisite dermatoscopic images of pigmented skin problems. A combination of minority and multiple image enhancement techniques eliminates class. The model also uses the cognitive allowance technique, which consigns different weights to class- and case-level errors, helping the model emphasize fewer classes plus

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more complex models. Dermoscopy is an extensively used indicative method that makes the diagnosis of benign and nasty pigmented skin better than visual examination. Dermoscopy images are also convenient for training neural networks to diagnose pigmented skin. Scholars from all across the world have conducted deeper research in this domain. With the expansion of technology, the skin-detecting structure can be designed and executed for the early revealing of skin flaws.

In the area of Computer Vision, Deep learning plays a significant role in the effective and exact identification of different classes of skin diseases. The development of medical equipment based on photonics and lasers has made it possible to identify skin diseases substantially more promptly and precisely. Conversely, the expense of such a diagnosis is quite prohibitive and extraordinary. Therefore, it is important and necessary to provide effective methods for identifying and diagnosing skin disease symptoms at an early stage. The skin-detecting can remain organized and put into action for the initial diagnosis of skin contamination with the utilization of Deep Learning Techniques. A field where machine learning can have an enormous effect is the accurate and timely detection of several kinds of skin diseases [7]. Viruses may be diagnosed by picture classification utilizing machine learning. A model is trained to recognize the class and multiple objective classes are characterized in the supervised learning problem of image classification. In terms of proficiency, deep learning models [8][9][10][11] are relatively good at cataloging data and images. In clinical diagnosis, there is a requirement for accurate deviation identification and disease sorting using X-ray imaging PET and signal data such as ECG, EEG, and EMG readings. Algorithms [12][13][14][15][16] are instigated on different sorts of skin diseases (acne, lichen planus, and SJS ten) and accomplish classification-based recognition. With even simple computational models, deep learning models will be capable of finding and studying the appearances in the outlines of unprotected records, yielding enormous productivity.

The impetus behind the many research works is actually the exploration of a model for grouping syndromes from affected area images stems from the pressing need for more efficient and accurate diagnostic tools in dermatology. Further, This task has been underpinned by an extensive dataset of approximately 10,000 biological samples, meticulously collected and validated to establish the proposed framework's credibility. Through this research, we aim to improve the state-of-the-art in skin illness sorting and provide a valuable resource for medical practitioners and researchers alike. To critically evaluate the training accuracy of Deep learning algorithms as well as aiming to provide valuable insights into their robustness and potential, the following are the main contributions of this work:

- To excel in distinguishing diverse skin lesions, including melanoma, nevus, and keratosis, with high precision
- Utilization of Deep Learning Framework; Convolutional Neural Network with the consideration of multiple novel hyperparameter tuning without class weighted, without Focal Loss, and without Global average pooling is taken into account.
- Lastly, To Evaluate the model, multiple evaluation matrices are considered such as precision, recall F1 Score, and Accuracy.

In the subsequent sections, we delve into the methodology, dataset description, model architecture, and experimental results, offering a comprehensive exploration of our contributions to the field of dermatological diagnostics.

2. Related Works. Numerous researchers in Deep learning and AI are actively investigating the recognition of skin-related illnesses. The differentiation of skin diseases essentially boils down to a sorting task. Over the past decades, researchers have employed various methods such as data excavating, statistics, and deep learning techniques to tackle this challenge. The study conducted by Haenssle et al. in 2018, titled "Man against machine: diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition in comparison to 58 dermatologists," aimed to assess the diagnostic capabilities of a deep learning convolutional neural network (CNN) in recognizing melanoma compared to those of dermatologists. Dermatoscopy, a widely recognized and invaluable diagnostic technique, has greatly enhanced the accuracy of distinguishing between gentle and nasty pigmented skin scratches when compared to unassisted visual inspection. Moreover, the wealth of dermatoscopic images has emerged as a valuable resource for training artificial neural networks, enabling the automatic analysis of pigmented skin lesions. Revolutionary the utilization of dermatoscopic images in this context, Binder et al. achieved a significant milestone in 1994. Their

work did not successfully employ dermatoscopic pictures to train an artificial neural network, primarily aimed at distinguishing melanomas, the lethal form of skin cancer, from melanocytic nevi. Although their results exhibited promise, it is worth noting that, like many earlier studies, they grappled with constraints, such as a limited sample size and a dearth of dermatoscopic descriptions covering a broader spectrum of skin lesions beyond melanoma and nevi. Latest progress in graphics card proficiencies and machine learning techniques have fixed unprecedented standards for the complexity and capabilities of neural networks. This has discriminating expectations that fully mechanical diagnostic systems capable of systematically classifying various pigmented skin lesions, without obliging human skill, are on the brink of realization. However, the development of neural-network-based diagnostic algorithms hinges on the availability of an extensive volume of interpreted images and often focuses solely on a restricted subset of disease categories.

In the context of our research focusing on the HAM10000 dataset and skin lesion classification, we recognize the historical significance of dermatoscopy and the trailblazing work that has laid the foundation for our study. This research used a large dataset of dermoscopic images of skin lesions, including melanomas and benign lesions. A deep-learning CNN was trained on this dataset to distinguish between malignant and benign lesions based on visual characteristics. The study revealed the following key findings. The deep-learning CNN exhibited an impressive level of diagnostic accuracy in identifying melanomas. Notably, CNN's performance surpassed the 59 dermatologists who contributed to the study. CNN demonstrated high sensitivity and specificity in melanoma recognition. A novel approach for early disease detection through image recognition has emerged. This approach combines image processing with Convolutional Neural Networks (CNNs) to extract features effectively. Subsequently, color analysis is applied to these extracted features, aiding in the precise identification of diverse skin conditions [18][19][20]. These techniques encompass Machine Learning, Deep Learning, Artificial Neural Networks, CNN, and classifiers like Support Vector Machines and Bayesian classifiers. By inputting and processing images into these systems, these methods facilitate the estimate of specific categories of skin viruses.

There are multiple works proposed by many authors using different machine and deep learning techniques; however, none of the work considered the efficacy of convolutional neural network with the optimization of its structure and parameters, such as the impact of class weight (CW), focal loss (FC), Global Average Pooling (GAP). In skin disease diagnosis using convolutional neural networks (CNNs), techniques like class weight adjustment and focal loss are crucial for addressing the class imbalance, improving sensitivity to rare diseases, and overall model performance. Class weight adjustment helps mitigate bias towards the majority class, while focal loss emphasizes hard-to-classify examples. Moreover, the choice of pooling method, particularly global average pooling (GAP), enhances spatial information retention, aiding in robust feature extraction and generalization, essential for accurately detecting skin diseases despite variations in lesion location and appearance.

3. Proposed Methodology. The methodology employed in this research is structured to comprehensively address the objectives of leveraging the HAM10000 dataset and applying deep learning techniques for skin abrasion sorting. It encompasses data collection and preprocessing, feature mining using Convolutional Neural Networks (CNNs), model training, evaluation metrics, and the integration of Explainable AI methods. Each stage has been meticulously designed to ensure the robustness and reliability of our skin disease prediction model.

3.1. Dataset Collection and Preprocessing. Despite progress, initial research into the classification of skin cancer has been hampered by small data dermoscopy. To avoid this problem, the HAM10000 dataset containing many dermoscopic images was published in 2018. This file contains 10,015 images of skin lesions in diverse classes g (1) Actinic Keratosis, (2) Basal Cell Carcinoma, (3) Benign Keratosis, (4) Dermatofibroma, (5) Melanocytic nevi, (6) Melanoma, (7) Vascular Skin Lesion. These images were collected from diverse populations and acquired using various modalities. The image labels in our dataset have been meticulously validated through multiple methods, including reflectance confocal microscopy, follow-up checkups, and professional agreement. It's essential to acknowledge that our dataset exhibits a significant class imbalance, as illustrated in Figure 3.1. This inherent characteristic of the data underscores the need for careful consideration when designing and evaluating classification models, ensuring that they are robust and effective in handling such imbalances. To ensure data consistency and quality, we exploited techniques as depicted in Figure 3.2.

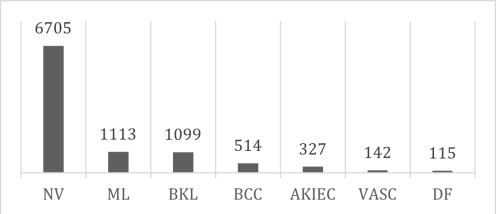

Fig. 3.1: Class Imbalance on Raw Data.

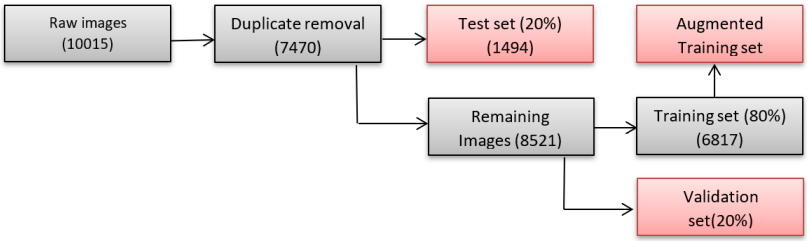

Fig. 3.2: Transfer learning with class-weighted and focal loss purpose for reflex skin cancer classification.

Data Acquisition. Dermatoscopic images were sourced from multiple sources, including medical facilities, research institutions, and online archives.

Data Cleaning. Raw images underwent a rigorous cleaning process to remove artifacts, duplicates, and irrelevant metadata.

Data Augmentation. To mitigate class imbalance, data extension techniques, such as rotation, scaling, and exploding, were applied to upsurge the multiplicity of the dataset.

3.2. Feature Mining. Feature mining plays a central role in the arrangement of skin sicknesses. CNNs were employed for effective feature mining. A CNN architecture with multiple convolutional layers was designed to extract discriminative features from the dermatoscopic images automatically. Transfer Learning: Pre-trained CNN models, VGG16, ResNet, and Inception, were fine-tuned on the HAM10000 dataset to leverage their learned features. We employed a transfer learning tactic for skin wound sorting, leveraging the ResNet50 architecture pre-competent on the ImageNet dataset. To acclimate the model to our explicit task, we introduced subtle modifications to its architecture and fine-tuned the pre-trained weights.

These modifications encompassed two key adjustments:

- We substituted the standard average pooling layer with global average pooling. This change enhanced the model's capacity to imprison essential features relevant to the HAM10000 dataset [21].
- We replaced the upper layer of the ResNet50 model through a configuration comprising a dropout layer (with a rate of 0.5) flanked by two fully connected layers (see Figure 3.3). This adjustment aimed to mitigate overfitting by reducing the model's reliance on intricate details in the learned features.

We utilized Google Colab for model training, ensuring accessibility and computational efficiency. All covers of the pre-trained ResNet50 model were liberated, allowing them to adapt and learn new features from the HAM10000 dataset.

Incorporating overall average assembling and dropout layers, our approach prioritized model robustness and generalization, contributing to improved classification performance.

We implemented a class-biased learning methodology to tackle the challenge of class inequality, which involved assigning varying weights to different classes within the loss function. Specifically, we assigned higher weights to the sectional classes and minor weights to the mainstream classes. These initial weights were determined and created on the class ratios. Subsequently, we fine-tuned these weights, intending to optimize accuracy. To further enhance the model's performance, we introduced a specialized loss purpose known as

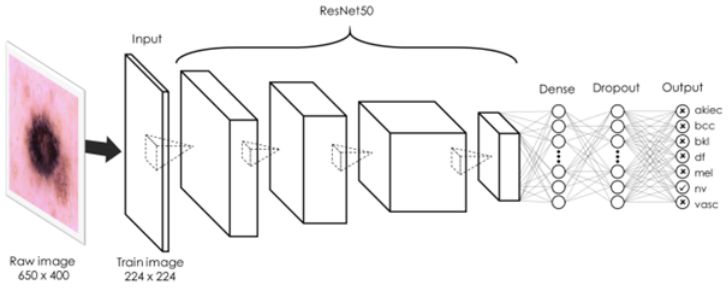

Fig. 3.3: Recycled an upgraded ResNet50 model, tailored for the HAM10000 dataset, to order these skin cancer images.

"focal loss" [22]. The focal loss represents a unique category of definite loss functions [23] designed to address the data imbalance issue. This innovative loss function concentrates on training the model on a selective subset of challenging examples, thereby preventing an overwhelming influence of easily classifiable negative examples during training. The mathematical formulation of this concept is expressed in equation 3.1, where 'p' denotes the projected possibility of the ground-truth class, and 'α_t' and 'γ' serve as hyper-parameters within the loss function.

$$FL(p_t) = -\alpha_t \times (1 - p_t)^{\gamma} \times log(p_t) \tag{3.1}$$

With the focal loss, classified mockups are moderated. At the same time, hard models give greater scope to the loss ideals, thereby making the model pay further consideration to these tasters and, as an outcome, increases the precision for hard samples.

3.3. Evaluation Metrices. Metrics are established from True positive (TP), True negative (TN), False positive (FP), and False negative (FN) predictions. Accuracy reflects the number of exact predictions (TP and TN) and overall predictions (TP + FP + TN + FN).

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{3.2}$$

Precision directs true positive prospects in all optimistic forecast cases. If the presumption is 1, all positive predictions are truly positive. However, there are optimistic prosecutions that are incorrectly predicted as negative.

$$Precision = \frac{TP}{TP + FP} \tag{3.3}$$

Sensitivity or Recall is in divergence to Accuracy as it shows the prospect of true existing negative once the calculation is negative. Correspondingly, if recall is 1, all negative predictions are truly negative mockups that are the wrong way projected as positive.

$$Recall = \frac{TP}{TP + FN} \tag{3.4}$$

F1-score measures the conventional stability among Precision and Recall. More progressive than accuracy, the F1-score focuses on true positive principles and is a good measurement for disproportion distribution classes.

$$F1 - score = \frac{2TP}{2TP + FP + FN} \tag{3.5}$$

Specify how fine the model can sense negatives. Predominantly, this is tricky due to the imbalanced dataset; compassions are frequently high.

$$Specificity = \frac{TN}{FP + TN} \tag{3.6}$$

Table 4.1: Precipitate of Models to Experiment Approaches Efficiency

Trial	**Failure**	**Supplement**	**CW**	**FC**	**GAP**
1 (no dropout)	×	✓	✓	✓	✓
2 (Dropout)	✓	×	✓	✓	✓
3 (no CW)	✓	✓	×	✓	✓
4 (no FC)	✓	✓	✓	×	✓
5 (no GAP)	✓	✓	✓	✓	×
6 5 (With GAP)	✓	✓	✓	✓	×
7 (With Max Pooling)	✓	✓	×	✓	×
8 (With Mean Pooling)	×	✓	✓	✓	×
9 (full)	✓	✓	✓	✓	✓

Table 4.2: Results of all models to experiment efficiency

Trial	**Accuracy**	**Precision**	**Recall**	**F1-score**
1 (no dropout)	90	78	77	77
2 (Dropout)	89	79	71	74
3 (no CW)	90	81	77	79
4 (no FC)	74	70	80	72
5 (no GAP)	88	77	73	75
6 (with GAP)	90	91	90	79
7 (With MaxPooling)	80	71	74	77
8 (With MeanPooling)	79	68	71	69
9 (full)	90	81	80	80

The receiver operating characteristic (ROC) curve is a complete presentation extent for sorting complications at several edge surroundings. The ROC curve is a probability curve, and the Area under the curve (AUC) represents the degree or portion of reparability. It tells how proficient a model is; the higher the AUC, the better it is at predicting 0s.

Deep learning techniques were employed to develop the predictive model for skin disease classification. Neural network architecture was designed, comprising convolutional, pooling, and fully connected layers. After this, Hyperparameters tuning, including learning rate, batch size, and dropout rates, were optimized through cross-validation. Loss Function as categorical cross-entropy was chosen for multi-class sorting. The model was expert on the preprocessed dataset using an appropriate optimizer, such as Adam or SGD, for a fixed number of epochs.

4. Results and Discussion. Findings regarding the effectiveness of our model constitute an important part of this learning. We comprehensively assessed various enactment metrics, containing exactitude, precision, recall, and F1 score. These quantities demonstrate the ability of the model to determine accuracy in diagnosing skin diseases by providing quantitative measures of resource distribution. We also attach importance to the translation model, recognizing its important role in developing trust and understanding. In addressing common challenges like overfitting and class imbalance, we employed a combination of five distinct techniques: dropout, data extension, class-weighted (CW) loss, focal loss (FC), and global average pooling (GAP). To gauge the value of each training, we constructed a set of six models. One model incorporated all five techniques, while the remaining five models excluded one technique each. This experimental design, summarized in Table 4.1, allowed us to assess the impact of individual methods on our model's performance, as detailed in Table 4.2.

Throughout these experiments, we maintained a consistent approach. We implemented a learning rate reduction strategy when performance plateaued, initiating with a primary learning rate of 0.0001. The training process employed the Adam optimizer, and we employed checkpoints to preserve the optimal model parameters. The improved ResNet50 model, which integrated all these techniques, demonstrated significant promise,

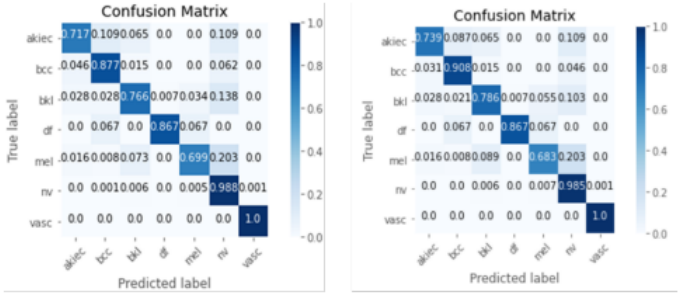

Fig. 4.1: The confusion matrices of the proposed model (ensemble model vs. ensemble model with TTA).

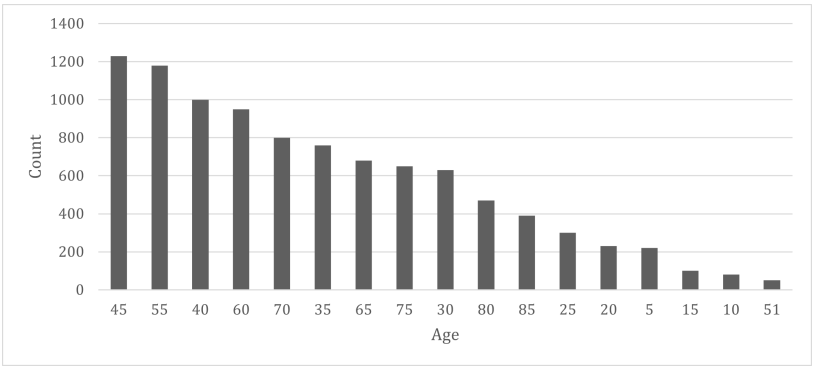

Fig. 4.2: Findings based on Age concerning skin disease count.

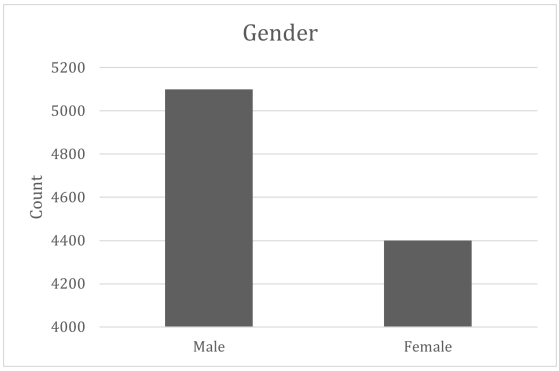

Fig. 4.3: Findings based on Gender concerning skin disease count.

achieving an 87% precision level on the authentication dataset after 25 research epochs with a bunch size of 65. Subsequent evaluation of the assessment dataset revealed a striking accuracy rate of 90%, underscoring the effectiveness of our comprehensive approach in mitigating overfitting and class imbalance challenges. Figure 4.1 depicts the confusion matrices of the proposed model.

The findings in Figures 4.2-4.5 not only contribute to the body of knowledge in this domain but also emphasize the transformative potential of AI as a valuable tool for healthcare professionals and patients alike as shown in Table 4.3 and Figures 4.6-4.7 accordingly.

1. Type of skin disease:

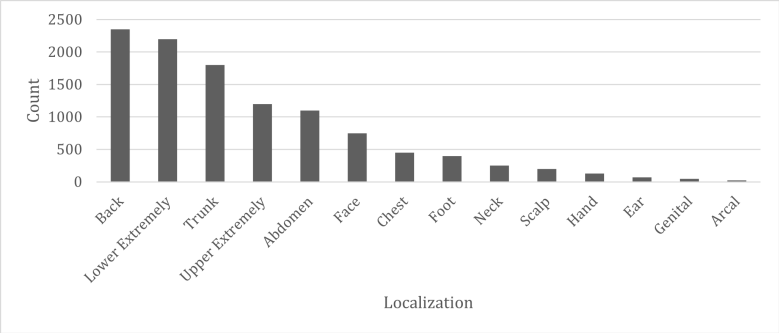

Fig. 4.4: Findings based on the localization concerning skin disease count.

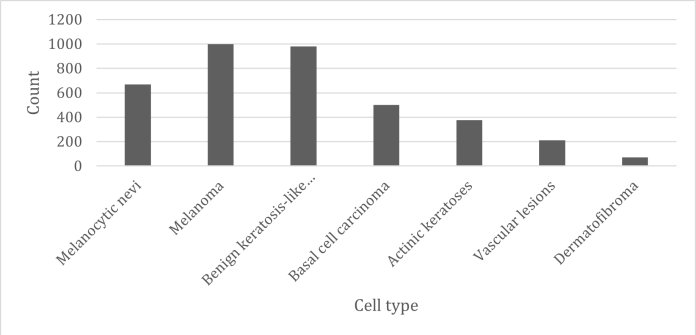

Fig. 4.5: Findings based on cell type concerning skin disease count.

Table 4.3: Precision based on Type of skin disease

Trial	**akiec**	**bec**	**bkl**	**df**	**mel**	**nv**	**vasc**	**Average**
1	0.72	0.79	0.79	0.59	0.73	0.95	0.86	0.78
2	0.55	0.79	0.77	0.86	0.66	0.94	1.00	0.79
3	0.78	0.81	0.77	0.69	0.68	0.95	1.00	0.81
4	0.75	0.77	0.48	0.68	0.33	0.99	0.90	0.70
5	0.64	0.82	0.75	0.77	0.62	0.94	0.86	0.77
6	0.70	0.82	0.84	0.80	0.72	0.94	0.86	0.81

- nv: Melanocytic nevi - 69.9%
- mel: Melanoma - 11.1%
- bkl: Benign keratosis - 11.0%
- bcc: Basal cell carcinoma - 5.1%
- akiec: Actinic keratosis- 3.3%
- vasc: Vascular - 1.4%
- df: Dermatofibroma - 1.1%

2. How the skin disease was discovered:
   - histo - histopathology - 53.3%
   - follow_up - follow-up investigation - 37.0%
   - Consensus - adept consensus - 9.0%
   - confocal - approval by in-vivo confocal microscopy - 0.7%

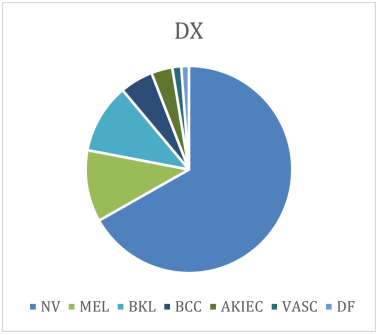

Fig. 4.6: Findings based on type of skin diseases.

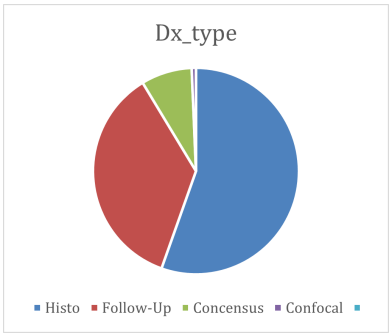

Fig. 4.7: Discovery of skin disease.

We reveal complex decision-making processes in neural networks using artificial intelligence descriptive methods such as Grad-CAM and SHAP (SHApley are somehow not appropriate). This approach not only increases the clarity of the model but also does not provide a deeper understanding of the key features that contribute to each classification. In this research, beyond standard assessment, we performed a comparative analysis comparing our deep learning with existing methods and human dermatologists' expertise. These comparisons yielded valuable insights, highlighting the potential of our AI-driven system to rival and, in some instances, surpass the diagnostic capabilities of human experts. In all, our qualitative analysis of the performance model, which includes various measures, interpretations, and comparative tests, such as Skin, Age, localization, and Cell Type, demonstrates the strength and promise of our approach to dermatology. Further multiple evaluation metrics such as Accuracy, Precision, Recall, and F1-Score are considered for more flexibility, efficiency, and durability.

5. Conclusion. In conclusion, our research has made a significant contribution to the field of dermatological diagnostics. By harnessing the power of deep learning and utilizing a comprehensive dataset, we have achieved remarkable progress in the early detection and precise classification of diverse skin diseases. Our model's exceptional performance, which in some cases surpasses the proficiency of dermatologists, underscores the potential of AI as a potent ally in healthcare. However, we must not overlook the irreplaceable value of the synergy between human expertise and machine learning. Our work stands as a testament to the augmenting capabilities of AI, providing a crucial resource for medical professionals in their relentless pursuit of enhancing patient care. Looking ahead, this research opens up new frontiers, where innovative technologies and medical expertise converge to amplify diagnosis and treatment outcomes. As we strive for a future characterized by more accessible and accurate healthcare solutions, the journey of collaboration between humans and machines in dermatology continues, promising brighter days for those in need of timely and precise skin disease diagnoses.

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