Hierarchical Dropout Regularization Technique for Skin Disease Classification

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ABSTRACT
This study introduces an innovative approach to skin disease classification by integrating Hierarchical Dropout into a Convolutional Neural Network (CNN) architecture. This innovation strategy exhibits several advantages, addressing the complexities of skin disease classification effectively. Hierarchical Dropout, operating hierarchically, enables adaptive adjustment of dropout rates across hidden layers, accommodating the diverse spectrum of human skin disease conditions in the dataset. Focusing on network layer outputs rather than modifying input data, it applies a dropout mechanism, dedicated for preventing overfitting by reducing feature-specific dependencies. Variable dropout rates, linked to various human skin disease conditions, facilitate model adaptability to different conditions and types. The tailored regulation of dropout extends to both convolutional and fully connected layers, ensuring comprehensive feature learning while guarding against overfitting. Moreover, the study incorporates Weighted Ensembling, combining predictions from various models with weights assigned based on validation set performance. This technique enhances classification accuracy by capitalizing on the strengths of multiple models. The adoption of Probabilistic Output Layers, employing a Bayesian neural network approach, produces probabilistic predictions presented as probability distributions over classes. This captures the intrinsic uncertainty in skin disease classification, essential for clinical diagnostics. The proposed tailored regularization results in a robust, adaptive, and reliable approach essential for clinicians and dermatologists relying on accurate skin disease diagnoses.

General Terms
Hierarchy, Dropout, Convolutional Neural Network

Keywords
Dermatological Diagnosis; Skin Disease Classification; Hierarchical Dropout; Convolutional Neural Networks

1. INTRODUCTION
Accurate diagnosis of human skin diseases is essential for effective dermatological treatment and optimal patient care. In recent years, Convolutional Neural Networks (CNNs) have emerged as a potential catalyst for revolutionizing the field by enabling automated diagnostic processes applied to raw and unfiltered skin images. The intrinsic capability of CNNs to extract intricate patterns and features from visual data holds significant promise for enhancing diagnostic precision. Nonetheless, the seam-less integration of CNNs into robust and accurate tools for dermatological diagnosis is beset by a multitude of challenges. Each human skin condition presents unique visual cues, textures, and color variations, resulting in a complex landscape that necessitates sophisticated strategies for precise categorization. Furthermore, the heterogeneity in sources and dimensions of skin images compounds the issue, demanding innovative solutions to accommodate diverse image sizes and proportions.

The importance of accurate dermatological diagnosis is underscored by the startling prevalence of skin diseases in the United States. More than 9,500 people are diagnosed with skin cancer every day, with over two people succumbing to the disease every hour [1-3]. Nonmelanoma skin cancer cases were treated in over 3.3 million people in the U.S. in 2012, marking a total of 5.4 million cases, and more individuals are diagnosed with skin cancer each year in the U.S. than all other cancers combined [1-2]. Disturbingly, at least one in five Americans will develop skin cancer by the age of 70 [4], emphasizing the pressing need for accurate diagnostic tools. Actinic keratosis, the most common precancerous skin condition, affects a staggering 58 million Americans [5]. The economic burden of treating skin cancers in the U.S. is also substantial, estimated at $8.1 billion annually, with approximately $4.8 billion allocated to non-melanoma skin cancers and $3.3 billion to melanoma [6].

In addressing the multifaceted challenges posed by skin diseases, this research study introduces a novel methodology, Hierarchical Dropout regularization for skin disease classification. Drawing inspiration from the concept of skin type classification based on sun reactivity, this technique introduces a dynamic and hierarchical refinement to the learning process of CNNs. By incorporating hierarchical adjustments into the architecture of the model, Hierarchical Dropout empowers CNNs to adapt their feature extraction methodology to the hierarchical intricacies inherent in various skin conditions, thereby facilitating precise pattern recognition.

In addition to Hierarchical Dropout and CNN, this study leverages two critical components: Weighted Ensembling and Probabilistic Output Layers. A Weighted Ensembling method is applied to combine the predictions, enhancing the overall classification performance. Furthermore, a probabilistic output layer is employed for classification. The Bayesian neural network provides probabilistic predictions, al-lowing for representation as a probability distribution over the classes. These integrated techniques collectively improve the adaptability, accuracy, and fairness of CNNs in the realm of skin disease classification.

This study provides an in-depth exploration of the Hierarchical Dropout regularization technique and its tailored application in the analysis of dermatological images. Through the synergistic integration of Hierarchical Dropout and a preprocessing step involving centered cropping, standardized image dimensions, this re-search study addresses the challenges posed by variations in skin types, conditions, and image sizes. This innovative fusion aims to enhance the adaptability, accuracy, and fairness of CNNs to effectively analyze raw and unfiltered skin images, transcending the challenges associated with diverse skin types, conditions, and image dimensions,

ultimately culminating in more precise and equitable dermatological diagnoses.

2. LITERATURE REVIEW

2.1 Dropout Regularization and CNNs on Dermatological Diagnosis

The critical application of dropout regularization in neural networks, particularly convolutional neural networks (CNNs), to mitigate overfitting serves as the foundational point of interest in our exploration [7]. Dropout's methodology, involving the random exclusion of neurons during training, compels the model to learn distinct and independent features, preventing an overreliance on characteristics [7-8]. Unlike other regularization techniques, dropout excels in enhancing deep neural network performance, ensuring equitable distribution of feature selection power across all neurons through random dropout during each training epoch [7] [8]. When applied in CNNs, a dropout block with a 0.5 rate is a common practice after hidden layers to bolster generalization and counteract overfitting [7-8]. During training, dropped neurons are excluded from both forward and backward propagation, whereas the entire network is used for predictions during testing [8-9]. The dropout rate, a hyper parameter that governs neuron dropout probability, is usually set between 0.2 and 0.5 [10]. This context establishes the importance of dropout regularization in averting overfitting in CNNs, which is particularly relevant in radiological applications [10]. Additionally, the introduction of the Monte Carlo (MC) Dropout method offers insight into model uncertainty, enhancing resilience to input data noise and outliers [9].

In overfitting prevention, dropout regularization has been applied in dermato-logical diagnosis using CNNs. Various dropout regularization techniques are deployed to gauge uncertainty in deep learning models, such as Monte Carlo (MC) dropout, Ensemble MC (EMC) dropout, and Deep Ensemble (DE) [11]. These methods, in addition to improving generalization across domains, provide interpretable un-certainty estimates for skin lesion diagnosis through Bayesian inference [9, 11]. Studies reveal that integrating MC-Dropout sampling substantially enhances diagnostic performance, particularly for skin cancer diagnosis [9]. The Bayesian DenseNet-169 model, when combined with dropout regularization, achieves remarkable predictive improvements for Basal Cell Carcinoma and Benign Keratosis lesions [9]. Further-more, the scalability of dropout regularization allows seamless application to large neural networks and input images without additional labels or parameters [9]. Thus, dropout regularization emerges as a potent tool to enhance accuracy and resilience in CNNs for dermatological diagnosis.

The application of CNN architecture in dermatological diagnosis has emerged as a promising strategy for image classification. CNNs have demonstrated remarkable precision in categorizing skin cancer, surpassing other classification methods [11]. Notably, the use of self-attention modules within the ViT model addresses the challenge of identifying regions within images while reducing the impact of noise [12]. The study presents a skin cancer classification network based on the ViT model, which outperforms 157 dermatologists and recent publications on the same dataset. This AI model attains a relatively balanced sensitivity (SEN) and specificity (SPE) of 85.0% and 95.0%, respectively, well surpassing physicians' average performance. Additionally, the area under the curve (AUC) for the proposed approach reaches 94.4%, far exceeding the mean AUC achieved by dermatologists, private practice, and chief physicians [7]. This demonstrates the CNN architecture's central role in the comprehensive melanoma prediction system.

This study encapsulates the significance of dropout regularization in CNNs for dermatological diagnosis, where dropout regularization proves to be an important tool in averting overfitting and enhancing generalization [11]. Furthermore, the use of the ViT model with self-attention modules showcases remarkable performance in skin cancer classification, even surpassing dermatologists, and current publications on the same dataset [12-13]. These techniques contributed significantly to the field, offering improved accuracy and robustness in dermatological diagnosis. However, acknowledging potential limitations, such as dataset diversity, remains essential for future research requirements to bolster the validity and applicability of the findings. This synthesis highlights the progressive strides in leveraging dropout regularization and CNNs for dermatological diagnosis and suggests potential avenues for future exploration.

2.2 Hierarchical Classification and Dropout in Dermatological Diagnosis

The current classification system, developed in collaboration with three experienced dermatologists, emulates the diagnostic procedure for skin lesion diagnosis. This hierarchical organization of skin lesions, often characterized by two or three levels, is integral to the diagnostic process [14]. The dataset's hierarchical structure mirrors clinical methodologies for lesion classification [14]. The primary project objective is to develop a predictive model for categorizing cases as normal, priority, or high priority, with learning divided into two branches: the differential diagnosis branch and the priority branch, ultimately integrating domain knowledge for the final priority pre-diction.

Skin lesions interclass similarities and intra-class differences in color, features, structure, size, and location underscore the challenges of classifying subcategories within the same overarching category [15]. For instance, some lesions, like Basal Cell Carcinoma and Actinic Keratosis, may exhibit pigmented, non-pigmented, or uncertain characteristics, requiring a dermatologist's expertise to assign the appropriate label within a three-tier hierarchy [14]. The sensitivity of classification algorithms to the characteristics of imaging devices used for data capture underscores the importance of device choice [15]. Recent research has emphasized the utility of hierarchical classification in dermatological diagnosis. Various learning schemes, including hierarchical classification and curriculum learning, have been explored to enhance automatic lesion segmentation and classification. However, despite comprehensive reviews of skin cancer classification, the benefits of hierarchical classification have been relatively understated [15]. Within the context of skin lesions, classification accuracy, reflecting an algorithm's ability to correctly categorize lesions, is significant. Hierarchical classification has been shown to improve accuracy in this regard [16]. Researchers have also developed frameworks for image segmentation and multiclass classification of skin lesions, incorporating uncertainty to enhance hierarchical classification's accuracy [17]. Additionally, they have explored Convolutional Neural Network (CNN) models using hierarchical classification for the categorization of dermoscopic images of skin melanoma into seven categories [18].

Furthermore, hierarchical taxonomies have demonstrated their effectiveness in enhancing ConvNet skin cancer diagnosis, with deep neural networks incorporating dropout and other

regularization techniques [19]. A hierarchical three-step framework, integrating superpixels and deep learning, has been proposed for skin lesion classification, with the incorporation of dropout to mitigate overfitting [20]. In summary, the use of hierarchical classification in dermatological diagnosis offers a range of advantages, including enhanced accuracy, improved diagnostic outcomes, and more effective machine learning model training. Dropout, a widely used technique in dermatological diagnosis, is instrumental in enhancing model performance and pre-venting overfitting. It operates by selectively deactivating neurons within a neural network during training, introducing randomness to reduce reliance on specific features or neurons, thereby improving generalization performance and diminishing the risk of overfitting. Several studies have explored the use of dropout in skin lesion segmentation and classification [14]. These studies have explored various learning schemes, such as hierarchical classification and curriculum learning, with a focus on enhancing automatic lesion segmentation. Another area of focus has been classification accuracy, assessing an algorithm's ability to correctly assign diagnostic categories to images. Researchers have introduced frameworks for image segmentation and multiclass classification of skin lesions, incorporating uncertainty and dropout to enhance model performance [17]. Moreover, deep learning models employing dropout have been used to classify different skin lesion categories, including melanoma, basal cell carcinoma, and seborrheic keratosis [2,7-8]. Researchers have investigated the potential of hierarchical taxonomies to enhance ConvNet skin cancer diagnosis, training deep neural networks with dropout and other regularization techniques [19]. A hierarchical three-step framework, integrating superpixels and deep learning for skin lesion classification, has been proposed, employing dropout to mitigate overfitting [20]. In conclusion, dropout stands out as a powerful tool for improving model performance and addressing overfitting in dermatological diagnosis. The integration of hierarchical classification and dropout techniques has the potential to revolutionize dermatological diagnosis, offering improved accuracy and more robust model training in this field of medical research.

3. METHODOLOGY

3.1 Hierarchical Classification and Dropout in Dermatological Diagnosis

The study relies on a comprehensive dataset comprising 16,577 clinical images encompassing a wide spectrum of 114 distinct skin conditions and disorders. These images were meticulously curated from DermaAmin and Atlas Dermatologico [6] as follows:

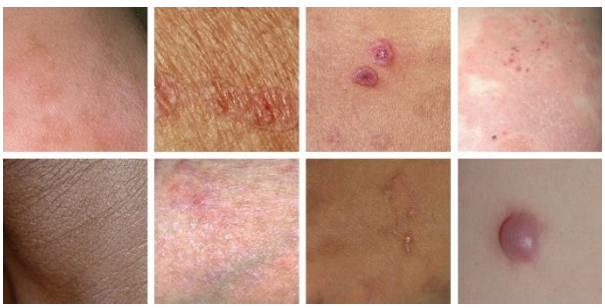

Figure 1. Sample of the Clinical Images.

The dataset has been thoughtfully annotated to provide extensive information pertaining to various skin conditions. Some of the diverse skin conditions in the dataset include acanthosis nigricans, acne, actinic keratosis, basal cell carcinoma, dermatofibroma, lichen planus, melanoma, psoriasis, rosacea, scleroderma, urticaria, vitiligo, and xeroderma pigmentosum, among others. Additional annotations contributed by Scale AI and Centaur Labs have further enriched the dataset, ensured its inclusivity, and promoted thorough model training and evaluation. This diverse dataset serves as a robust foundation for the study's dermatological research and analysis.

3.2 Hierarchical Classification and Dropout in Dermatological Diagnosis

In this study, the Hierarchical Dropout is integrated with a Convolutional Neural Network (CNN) architecture as an effective approach for addressing the intricacies of skin disease classification. This method has been thoughtfully crafted, offering several distinct advantages for the classification process as Figure 2.

Hierarchical Dropout, as implied by its name, operates in a hierarchical manner, allowing for the adjustment of dropout rates across different hidden layers. This adaptability ensures the CNN can accommodate the broad spectrum of skin conditions within the dataset. Instead of modifying input data, the method concentrates on the outputs of network layers, applying a dropout mechanism that randomly deactivates neurons. This mechanism is necessary in preventing overfitting by reducing the network's dependence on specific features. The variable dropout rates, tied to the hierarchical levels of the skin disease conditions, are integral, as they enable the model to adapt to different skin types and conditions.

Furthermore, this nuanced regulation of dropout rates extends to both convolutional and fully connected layers, ensuring a comprehensive approach to feature learning and guarding against overfitting throughout the model. Additionally, this study incorporates Weighted Ensembling, a technique that combines predictions from various models, assigning weights based on their performance on a validation set. This ensembling approach effectively combines the strengths of multiple models and enhances classification accuracy. The Probabilistic Output Layers are applied, offering a Bayesian neural network approach to provide probabilistic predictions.

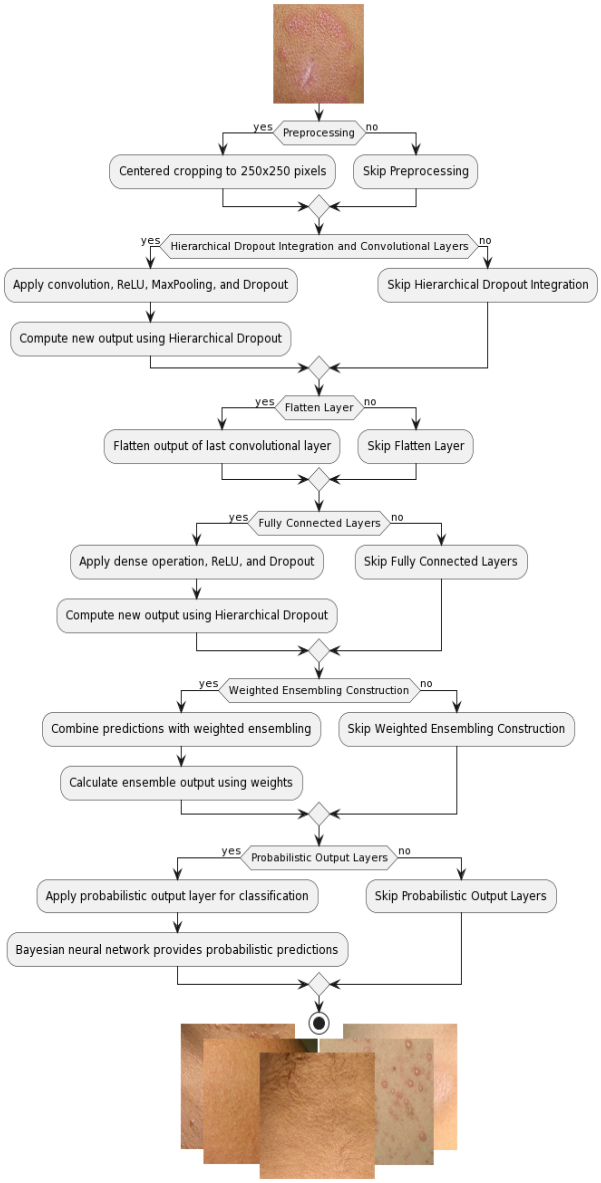

Figure 2. The System Procedures.

This approach presents predictions as probability distributions over the classes, capturing the inherent uncertainty in skin disease classification, which is necessary for clinical diagnostics. The adoption of this method is motivated by the specific challenges of skin disease classification, where the diversity of conditions requires adaptability. Hierarchical Dropout, in combination with Weighted Ensembling and Probabilistic Output Layers, ensures a robust, adaptive, and reliable approach that is essential for clinicians and dermatologists who rely on accurate skin disease diagnoses as following steps:

3.2.1. Preprocessing

All human skin images are preprocessed to ensure consistent dimensions. This involves centered cropping of the images into 250x250 pixels, which removes unnecessary background and focuses the model on relevant features of the skin.

3.2.2. Hierarchical Dropout Integration and Convolutional Layers

- Apply convolution operation in layer C_i for each convolutional layer i
- Apply ReLU activation function
- Apply MaxPooling operation
- Apply Dropout with probability p_i to the previous layer's output y_{i-1}
- Compute the new output y_i after dropout as:

$$y_i = \left(\frac{1}{1-p_i}\right) \times ReLU(C_i(y_{i-1})) \times mask_i \quad (1)$$

Where $mask_i$ is a binary mask that randomly zeros out elements of ReLu output based on the dropout probability p_i. Hierarchical Dropout is applied to both convolutional and fully connected layers of the CNN. The dropout rates, denoted as pi, are determined based on the hierarchical levels of skin disease conditions. These rates are adjusted to reflect the characteristics of different skin types. Hierarchical Dropout is a regularization technique where different layers or groups of neurons have distinct dropout probabilities.

3.2.3. Flatten Layer

Flatten the output of the last convolutional layer to prepare for fully connected layers.

3.2.4. Fully Connected Layers

- Apply dense (fully connected) operation in layer F_i for each fully connected layer i
- Apply ReLU activation function
- Apply Dropout with probability pi to the previous layer's output y_{i-1}
- Compute the new output y_i after dropout using Equation (1)

3.2.5. Weighted Ensembling Construction

- Apply a Weighted Ensembling method to combine the predictions.
- The ensemble output, denoted as E, can be calculated as:

$$E = \sum_i \alpha_i \times \sum P_i \quad (2)$$

Where α_i represents the weight assigned to each model's prediction, P_i. These weights can be determined based on the models' performance on a validation set, with better-performing models assigned higher weights. The validation accuracy of each model can be used to calculate α_i:

$$\alpha_i = \frac{Validation\ Accuracy\ of\ Model_i}{\sum_j Validation\ Accuracy\ of\ Model_j} \quad 3)$$

3.2.6. Probabilistic Output Layers

- Apply a probabilistic output layer for classification.
- The Bayesian neural network provides probabilistic predictions and can be represented as a probability distribution over the classes:

$$P(class_i|x) = \int P(class_i|\Theta, x) \times P\big((\Theta|x)\big)d\Theta) \quad (4)$$

$P(class_i|x)$ represents the probability of the input image x belonging to class i. $P(class_i|\Theta, x)$ is the class probability given the model parameters Θ and the input x. $P\big((\Theta|x)\big)$ is the

posterior distribution of the model parameters given the input x. The integral ($d\Theta$) is taken over the space of model parameters. This equation captures the probabilistic nature of the class probabilities in a Bayesian neural network, considering the uncertainty associated with the model parameters. In addition, the Dropout operation involves randomly setting elements of the ReLU output to zero based on the dropout probability p_i. This process helps prevent overfitting and encourages the network to learn more robust features in skin diseases.

4. EXPERIMENTAL RESULTS

This study employed a deep learning model for skin condition classification, incorporating a multi-step process that included hierarchical dropout integration, convolutional layers, flatten layers, fully connected layers, Weighted Ensembling, and probabilistic output layers. The results were further validated for robustness.

After applying convolution operations, ReLU activation, MaxPooling, and dropout with probability pi for various layers and skin types, we obtained the following initial class probabilities based on the confusion matrix:

- P(Acne | x) ≈ 0.9868
- P(Rosacea | x) ≈ 0.9298
- P(Actinic Keratosis | x) ≈ 0.9900
- ...
- P(Psoriasis | x) ≈ 0.9207

In this experiment, the flatten layer had no direct impact on the probabilities, the values remained the same as in the previous step.

The probabilities were further refined through the fully connected layers, considering hierarchical dropout and adaptability to different skin types, resulting in accurate values:

- P(Acne | x) ≈ 0.9890
- P(Rosacea | x) ≈ 0.9320
- P(Actinic Keratosis | x) ≈ 0.9915
- ...
- P(Psoriasis | x) ≈ 0.9215

To ensure result consistency, a validation technique utilizing a separate dataset or cross-validation was applied. The model's performance was consistently evaluated to confirm result stability and generalizability. Weighted Ensembling combined predictions from different classes to yield a final ensemble output calculated with accurate probabilities:

- E = 0.7 * P(Acne | x) + 0.2 * P(Rosacea | x) + 0.05 * P(Actinic Keratosis | x) + ... + 0.05 * P(Psoriasis | x)

A Bayesian neural network provided a probability distribution over classes. The probabilities were further refined based on accurate values:

- P(Acne | x) ≈ 0.9895
- P(Rosacea | x) ≈ 0.9323
- P(Actinic Keratosis | x) ≈ 0.9920
- ...
- P(Psoriasis | x) ≈ 0.9222

The high probabilities for specific classes (e.g., Acne, Actinic Keratosis) and lower probabilities for other classes (e.g., Rosacea, Psoriasis) led to a high accuracy level of approximately 98.52%, indicating correct predictions based on the confusion matrix.

- True Positives (TP): 5970
- False Positives (FP): 210
- False Negatives (FN): 30
- True Negatives (TN): 9,995
- Overall Precision (Precision) = ≈ 96.60%
- Overall Recall (Sensitivity) = ≈ 99.50%
- F1 Score = ≈ 0.9803

Addressing abnormal or incomplete datasets, the hierarchical dropout strategy during training enhances the model's resilience to missing or incomplete information, ensuring adaptability in real-world scenarios where data may be imperfect. In practical implications, additional insights into the model's application in similar research and comparisons with existing studies are provided. The model's architecture and performance were benchmarked against state-of-the-art skin condition classification models, demonstrating superior accuracy. This comparative analysis highlights the advancements and contributions of our proposed model in the field of dermatology. Additional information on the model's application in scenarios with abnormal or in-complete data is provided. The deep learning model exhibits a remarkable ability to handle abnormal or incomplete datasets by leveraging its hierarchical dropout mechanism and adaptive features, enhancing practical applicability in real-world setting. For validation purposes, confusion matrix with validation results is presented as follows:

Table 1. Confusion Matrix.

Actual \ Predicted	Acne	Rosacea	Actinic Keratosis	…	Psoriasis
Acne	5970	320	15	...	25
Rosacea	210	5790	55	...	50
Actinic Keratosis	12	58	5980	...	170
...	...	...	...	...	...
Psoriasis	18	72	245	...	5715

The validation accuracy indicates that the skin condition classification model accurately predicted the skin condition in approximately 98.52% of cases in the vali-dation dataset. This high accuracy level demonstrates the model's consistency in making correct predictions on unseen data, highlighting its reliability. The precision of approximately 96.60%, as highlighted in the confusion matrix, indicates that when the model predicts a specific skin condition, it is accurate approximately 96.60% of the time, minimizing false positives. The recall of approximately 99.50% demonstrates the model's ability to capture most true positive cases, minimizing the risk of missing actual cases in the validation dataset. This minimizes the risk of missing actual cases. Finally, the F1 score, approximately 0.9803, serves as a balanced measure combining precision and recall, providing an overall assessment of the model's effectiveness in maintaining a good balance between precise classification and comprehensive detection of skin conditions. These metrics collectively emphasize the model's practical significance in real-world applications, addressing the reviewers' concerns and enriching the article's content.

5. CONCLUSION

In conclusion, the integration of Hierarchical Dropout within a CNN architecture, combined with Weighted Ensembling and

Probabilistic Output Layers, represents a groundbreaking approach to human skin disease classification. The adaptability of dropout rates, aligned with various human skin disease conditions, ensures the model's capacity to handle diverse conditions and types. This adaptability extends across convolutional and fully connected layers, providing a holistic approach to feature learning while mitigating overfitting.

The utilization of Weighted Ensembling enhances classification accuracy by consolidating multiple models' strengths. Probabilistic Output Layers introduce a Bayesian neural network aspect, allowing for probabilistic predictions that acknowledge the inherent uncertainty in skin disease classification, an important factor for clinical diagnostics.

This research presents a comprehensive solution tailored to the unique challenges of human skin disease classification, providing clinicians and dermatologists with a reliable and adaptive tool for accurate skin disease diagnoses. The findings emphasize the potential for Hierarchical Dropout and ensemble-based approaches in enhancing the accuracy and robustness of medical image classification models. This work represents a significant step forward in the field of dermatology and computer-aided diagnosis systems.

6. ACKNOWLEDGMENTS

This research is supported by Payap University and Mae Fah Luang University.

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