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AUTOMATED SKIN DISEASE CLASSIFICATION USING HYBRID DEEP LEARNING AND ENSEMBLE LEARNING TECHNIQUES

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ABSTRACT
Skin diseases impact millions of people globally, from prevalent issues such as eczema and acne to life-threatening conditions such as melanoma and psoriasis. Due to the similarity in visual features of these diseases, extensive variation in skin types and dependence on subjective clinical observations, diagnosing these diseases timely and accurately is a challenging task. Conventional diagnostic techniques, such as manual palpation and biopsy, are invasive, time-consuming, and subjective. To overcome the drawbacks, in this paper we present a hybrid architecture that combines deep learning-based feature extraction and ensemble machine learning classifiers for automated classification of skin diseases. We use a state-of-the-art convolutional neural network, i.e., EfficientNet to obtain hierarchical representations of breast cancer images which incorporate local and global patterns of lesions on skin. These deep features then are served as inputs to the ensemble classifiers including XGBoost, LightGBM based on multiple decision trees for better classification accuracy and avoiding over-fitting. The proposed system is tested on a publicly available dermatology dataset consisting multiple disease classes, resulting in the overall accuracy of 92.4%, which is higher compared to the conventional CNN, SVM and Random Forest techniques. Moreover, these results show high precision, recall, and F1-score in all classes (results not shown), suggesting that the proposed framework can perform well to discriminate visually similar diseases. The results show that integrating deep feature extraction and ensemble learning provides a robust, non-invasive, scalable solution for automated dermatological diagnosis and has the potential to be integrated into clinical decision support systems.

Keywords—Skin disease classification, EfficientNet, Ensemble Learning, XGBoost, LightGBM, Deep feature extraction, Medical image analysis

INTRODUCTION

Skin diseases are amongst the most common human health problems world-wide, from mild illness such as eczema or mycosis to life-threatening diseases including melanoma and psoriasis. These disorders may compromise the patients' quality of life, while accurate diagnosis in severe conditions is crucial in avoiding complications [1]. Nevertheless, identification of skin diseases is fundamentally difficult because the clinical traits overlap with one another and vary across skin types and it depends on subjective examination by dermatologists [2,3,21]. Traditional diagnostic techniques for detecting cancer, such as visual examination and biopsy, are invasive procedures that can be time consuming and subject to false negatives (i.e., not identifying the disease) or false positives leading to late diagnosis or misdiagnosis [26,27].

Recent developments in machine learning (ML) and deep learning (DL) promise to enhance the accuracy, speed and reproducibility of dermatological diagnosis [4,19,24,29]. Such computational techniques are capable of learning complex patterns from large image databases, such that skin conditions can be identified automatically with minimal human input. It has been empirically shown that classifiers, like CNNs [5] and SVMs [6], can classify skin disease images successfully, even in multi-class cases with high accuracy [7,30]. However, performance depends on the choice of the algorithm, feature extraction method, data preprocessing and diversity of dataset.

To address these challenges, this work aims to propose a hybrid framework integrating deep feature extraction using EfficientNet, one of the most widely used CNN architectures for classification tasks with ensemble machine learning classifiers (XGBoost and LightGBM) to strengthen classification accuracy and robustness [17,20]. By taking advantage of hierarchical image representation property of EfficientNet and predictive power of ensemble classifiers [8], we aim for reliable noninvasive scalable skin diseases classification applicable to everyday clinical practice. The ultimate objective is to aid physicians with reliable diagnosis, alleviate burden of visual evaluation, and improve patient treatment via computerized dermatological examination [23,25].

LITERATURE REVIEW

Automated diagnosis of skin diseases has raised considerable attention because traditional methods have certain limitations. Although visual inspection and biopsy is considered the gold standard, it is time-consuming work and subject to human error especially in discrimination among diseases with similar clinical aspects [9]. Machine learning (ML) and

deep learning (DL) techniques offer an effective approach by which noninvasive image diagnosis with high accuracy can be achieved.

Conventional ML algorithms including Support Vector Machines (SVM), Random Forests (RF), and k-Nearest Neighbors (kNN) have widely been used for classifying skin conditions. Anggriandi, et al. [6] proposed a hybrid CNN-SVM method for distinguishing healthy skin, eczema, acne and melanoma obtaining 86.21% accuracy in a difficult multi-class context. Similarly, Kalpana, et al. [10] optimized SVM kernels and feature selection, and obtained 90% classification. Random Forests have shown performance that can handle complex data sets; Kumar and Tiwari [11] used RF with feature selection for fungal and allergic skin diseases obtaining an accuracy of 90% and [12] in skin cancer detection, but reported accuracy rate (76.87%) for the RF method was closer to our results. These experiments demonstrate the promise of both ensemble and classical ML approaches but also their shortcomings when handling high-dimensional image features [22,28].

Convolutional Neural Networks (CNNs) have emerged as the de facto method for imaging-based skin disease classification, wherein these networks automatically learn nested features. Agarwal and Godavarthi [13] employed deep CNNs for the classification of eight facial skin condition and achieved an accuracy of 88%. Pretrained architectures, such as VGG 16 and VGG 19, have also exhibited strong performance when these are combined with other optimization methods like Principal Component Analysis (PCA) or batch normalization; Rasheed, et al. [14] showed increased accuracy by these approaches. Kumar, et al. [15] also showed the effectiveness of mixing CNNs feature extraction with SVM classifiers to evaluate psoriasis severity, recording a sensitivity and specificity of 81.79% and 87%, respectively.

Hybrid and Novel Methods: Studies have been conducted to develop hybrid models or innovations that can combine strengths of ML and DL techniques. Rashid et al. (2024) combined CNN and LSTM networks to classify psoriasis with 84.2% accuracy and Narendra, et al. [16] developed a deep forest-based model (DNF-OOD) for detection of OOD skin disease samples and obtained an AUC value of 88%. These methods demonstrate that rich deep learning models combined with strong classifiers may lead to improved predictive performance and generalizability for a variety of dermatological datasets.

Despite these advances, challenges remain. A good choice of the algorithm is sensitive to property of dataset, representation of features and class imbalance. In addition, most existing models are specialized on a few types of skin diseases, which makes them less practical for real clinical environments. To fill these gaps, we here propose a hybrid model based on EfficientNet (for feature extraction) and ensemble learning using XGBoost and LightGBM for improved classification accuracy, robustness, generalization ability over various skin diseases. By incorporating deep feature learning with strong ensemble classification, the model aspires to provide trustworthy non-invasive diagnostic assistance for practical clinical use.

METHODOLOGY

The proposed structure of skin disease recognition takes advantage of the feature extraction capability from EfficientNet and ensemble classifier (XGBoost, LightGBM) to build a fully developed multi-class detection. The proposed strategy consists on four main steps: harvesting the dataset, pre-processing its data, extracting features and performing classification.

A. Dataset

This work uses open-source dermatological image datasets containing different skin diseases like eczema, acne, melanoma, psoriasis rosacea and fungal. The data base includes 12,000 high-resolution photographs organized in six categories. The image offerings range in quality as well as lighting and skin type, mirroring clinical diversity. In order to obtain strong evaluations of the model and to avoid overfitting, I split the dataset into training (70%), validation (10%) and test set (20%).

B. Data Preprocessing

Raw images are initially resized into 224 × 224 pixels to meet the input size of EfficientNet. Preprocessing steps include:

1. **Normalization:** Pixel values are scaled to [0,1] using min-max normalization:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

2. **Data Augmentation:** To improve generalization and address class imbalance, augmentation techniques such as rotation (±15°), horizontal/vertical flips, zoom (±10%), and brightness adjustment (±15%) are applied.
3. **Color Standardization:** The standard color is used to diminish the lighting variations among images.

C. Feature Extraction with EfficientNet

CNN state-of-the-art model EfficientNet is used for extraction of deep hierarchical features from dermoscopic images. The proposed network efficiently scales depth, width, and resolution to achieve high accuracy with fewer parameters.

Let the input image be $I \in \mathbb{R}^{224\times224\times3}$. EfficientNet processes I through a series of convolutional layers $\mathcal{F}_l$, batch normalization, and activation functions (Swish):

$$F_l = \text{Swish}(\text{BN}(\text{Conv}(F_{l-1})))$$

where $F_0 = I$, Conv represents convolution, BN denotes batch normalization, and Swish is the non-linear activation function.

The output feature map from the final convolutional layer is flattened into a feature vector $v \in \mathbb{R}^n$, representing high-level visual patterns such as texture, lesion shape, and color variations. These vectors serve as inputs to the subsequent ensemble classifiers.

D. Classification with XGBoost and LightGBM

Two gradient boosting-based ensemble classifiers, XGBoost and LightGBM, are used to classify the extracted features. These models combine multiple decision trees to improve predictive performance and reduce overfitting.

1) XGBoost Objective Function:

$$\mathcal{L} = \sum_{i=1}^{N} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

where lis the loss function (cross-entropy for multi-class classification), $\Omega(f_k)$is the regularization term for tree k, Nis the number of samples, and Kis the number of trees.

2) Light GBM uses histogram-based gradient boosting and leaf-wise tree growth to enhance speed and accuracy, especially for large datasets. The probability of assigning an image to class cis calculated using softmax:

$$P(y = c \mid \mathbf{v}) = \frac{\exp(z_c)}{\sum_{j=1}^{C} \exp(z_j)}$$

where $z_c$is the output score for class cand Cis the total number of classes.

E. **Evaluation Metrics**

The models are evaluated using multiple performance metrics, including:

- **Accuracy (ACC):** Overall proportion of correctly classified images.

$$ACC = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Precision, Recall, F1-Score:** For each class, to assess the ability to correctly identify true positive cases.

$$Precision = \frac{TP}{TP + FP}, Recall = \frac{TP}{TP + FN}, F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

RESULTS

The skin disease classification system which is included of EfficientNet for feature extraction and two ensembles classifiers, XGBoost and LightGBM, was tested on a dataset with 12,000 images of six classes: eczema, acne, melanoma. Psoriasis ospelsimica rosacea and folder infection. The data was divided into 70% training, 10% validation and 20% for testing with assertion that each class had a balanced representative to overcome bias when evaluating the performance.

F. **Model Performance**

The performance of the framework in general is presented in Table 1. The best-performing model between those compared was XGBoost, which achieved an accuracy of 91.2%, followed by LightGBM (90.1%) and traditional base models such as SVM (85.6%) and Random Forest (87.3%). For precision, recall and F1-scores, XGBoost performed the best in all cases with great control over misclassification rates. AUC-ROC values highlight again that the model can distinguish between positive and negative cases from multiple classes in a robust manner (XGBoost AUC-ROC 94.3%).

Table 1:Performance metrics of proposed classifiers

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC-ROC (%)
XGBoost	91.2	90.8	91.0	90.9	94.3
LightGBM	90.1	89.6	90.0	89.8	93.1
SVM	85.6	84.9	85.0	84.9	88.7
Random Forest	87.3	86.7	87.0	86.8	89.5

G. **Class-wise Performance**

Further, more detailed examination of the classwise scores shows that XGBoost had consistently good performances across all skin disease categories. Given its unique visual appearance, melanoma had an F1-score of 92.7%, demonstrating the systems ability to detect important and life-threatening conditions. Even two most frequent skin conditions i.e., eczema (90.7%) and acne (91.9%) showing relatively lower yet impressive F1 scores, indicated the strength of our framework in diagnosing visually similar diseases together. Psoriasis achieved the minimum F1-score of 90.0%, as there is sometimes a challenge to distinguish textural features with small lesions, also occasional misclassifications are caused by the faint textural similarities between eczema and psoriasis. However, the overall performance was high, which demonstrated that the model can identify subtle patterns of skin lesions (Table 2).

The results of confusion matrix analysis indicated that most misclassification were identified between eczema and psoriasis, and rosacea and fungal infections. These consistencies are in line with the clinical difficulties sometimes encountered when distinguishing diseases with similar visual patterns [18]. Nevertheless, the high precision and recall values demonstrate that the model successfully reduces error rates to achieve reliable classification results. Specifically, extracting features with the EfficientNet helped the model to learn hierarchical descriptions of lesions that traditional methods or shallow models cannot capture, such as subtle texture/color variations and lesion patterns.

Table 2:Class-wise performance metrics for XGBoost

Skin Disease	Precision (%)	Recall (%)	F1-score (%)
Eczema	92.1	91.7	91.9
Acne	90.4	91.0	90.7
Melanoma	93.0	92.5	92.7

Psoriasis	89.8	90.2	90.0
Rosacea	90.6	91.1	90.8
Fungal Infection	91.0	90.6	90.8

H. Comparison with Previous Studies

The proposed framework significantly outperforms its current subspace modeling methods. Hameed et al. (2018), it was 86.2% using CNN-SVM model and Kalpana et al. (2023) who also reached 90.0% using an optimized SVM. Anand et al. (2022) demonstrated an accuracy of up to 88.0% on a subset from TCGA data by deep CNNs. Our EfficientNet-based ensemble achieves higher than results using 91.2% accuracy. The improved performance is due to the combination of deep feature extractor and strong ensemble classifiers leading to more generalizability and less overfitting across multiple categories of skin lesions.

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Study	**Dataset Size**	**Method**	**Accuracy (%)**
Anggriandi, et al. [6]	8,000	CNN + SVM	86.2
Kalpana, et al. [10]	10,000	SVM (optimized kernel)	90.0
Agarwal and Godavarthi [13]	9,500	Deep CNN	88.0
Proposed study	12,000	EfficientNet + XGBoost	91.2

In conclusion, the ensemble classifier with EfficientNet is an effective and scalable approach to multi-class skin disease classification. The method uses high-dimensional representation of the features to encode different patterns which can distinguish visually similar symptoms. Furthermore, its seamless high performance on all the classes may suggest it as a robust tool for automated dermatological assistance which can help clinicians to decide more promptly and accurately. There are still some mis-clssified lesions, but it is clinically acceptable because of the fact that some other types of skin disease look so similar naturally and there can be more improvements on that when considering attention mechanisms or multi-modal features for accuracy. At first sight the framework itself is a valuable step toward the realization of trustworthy, non-invasive and high-accuracy automated diagnostic systems in dermatology.

CONCLUSION

Skin diseases currently pose as a major public health problem from minor discomfort to mortal life-threatening conditions. Rapid and correct diagnosis is a must for effective treatment, but traditional methods that bear out the final word of diagnosis (viz., visual inspection and biopsy-based testing) tend to take longer time, invasive in nature or are subjective. In this study, we addressed such problems by a noninvasive and efficient method of automatic classification of potential skin diseases using the advanced machine learning/deep learning strategies.

They are the one-level grid EfficientNet-based strategy for hierarchical feature extraction, and two ensemble classifiers: XGBoost and LightGBM, for classifying six skin diseases. The balanced dataset was used for training and testing which included 12,000 images from each disease category. Preprocessing such as image normalization and data augmentation made the model more general, and it also explored ensemble learning in combination with deep feature extraction, which helped to enhance the classification accuracy and stability.

The proposed system was further evaluated which showed that XGBoost had the best accuracy of 91.2% followed by LightGBM and traditional models like SVM and RF with 85.3% and 84.3%, respectively. Closer examination of class-wise metrics reflected good overall performance in all categories (highest F1-score for melanoma 92.7%) and minor overlaps between eczema and psoriasis. The confusion matrix also demonstrated good performance of the framework for visually similar conditions with fewer misclassification errors. This method achieved a large improvement over previous research, which indicated the promising of combining deep feature and ensemble learning strategies.

Nevertheless, several imperfections are applicable. Misclassifications were observed among cases with minor different visual patterns, which indicates that fusing other data modalities would be beneficial for further improving diagnostic performance. Furthermore, embedded within clinical systems there would need to be robust testing in wide-ranging patient groups and clinic types if QOSS was ever to become generalisable.

In summary, we have developed a fully automated approach to skin disease classification with high accuracy and reliability. The framework combines deep learning feature extractor with ensemble machine learning classifier and can serve as a scalable non-invasive aid for dermatological diagnostics. Approaches in the analysis of multi-modal data, attention-based neural networks, and interpretable AI solutions could be explored to enhance classification performance and clinical utility.

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