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PATTERNED BASED SKIN DISEASE DETECTION WITH OPTIMIZED MACHINE LEARNING MODELS

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ABSTRACT

Skin diseases, ranging from common infections to life-threatening conditions such as melanoma, require timely and accurate diagnosis to ensure effective treatment and improved patient outcomes. However, conventional diagnostic methods often rely on dermatological expertise, which may be scarce in remote or resource-constrained regions. Recent advances in machine learning (ML) have enabled automated skin disease detection using dermoscopic and clinical images, showing performance levels comparable to expert dermatologists. Despite these successes, challenges such as high computational complexity, class imbalance, and poor generalization across diverse populations limit the practical deployment of these models. This study explores the use of optimized machine learning models for enhancing skin disease detection. Optimization strategies including transfer learning, hyperparameter tuning, model pruning, quantization, and ensemble methods are employed to improve model accuracy, reduce computational cost, and enable real-time inference on mobile and edge devices. Experimental results demonstrate that optimized models achieve superior classification performance while maintaining low latency and efficiency, thus making them suitable for integration into teledermatology and point-of-care diagnostic systems. The findings highlight the potential of optimized ML models in advancing accessible, reliable, and scalable skin disease detection solutions.

Keywords: Machine Learning, Support Vector Machine, Skin Disease, Decision Tree, Artificial Intelligence.

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I. INTRODUCTION

Skin diseases constitute a major global health concern, affecting millions of people across all age groups. Conditions such as acne, eczema, psoriasis, and melanoma not only impact quality of life but, in severe cases, can lead to life-threatening outcomes if not diagnosed early. Traditional diagnostic methods primarily rely on dermatologists' visual inspection and, when necessary, histopathological tests. While these approaches are effective, they are also subject to limitations including limited access to dermatological expertise, inter-observer variability, high costs, and delays in diagnosis, particularly in rural and resource-constrained regions. Recent advances in machine learning (ML) and deep learning (DL) have demonstrated significant potential in automating skin disease detection using clinical and dermoscopic images. Convolutional Neural Networks (CNNs) and their variants have achieved diagnostic accuracy comparable to, and in some cases surpassing, expert dermatologists. Publicly available datasets such as HAM10000 and the ISIC archive have accelerated research by providing large collections of annotated skin lesion images. However, despite these successes, several challenges remain before widespread clinical adoption can be achieved. The primary challenges include high computational demands, large model sizes, class imbalance in datasets, and poor generalization across diverse skin types and imaging conditions. Large deep learning models often require high-performance computing resources, which makes real-time deployment on mobile or edge devices impractical. This restricts their use in teledermatology and point-of-care applications, where lightweight, efficient, and accurate models are crucial. To address these challenges, researchers are focusing on optimized ML models that balance accuracy with efficiency. Optimization strategies include transfer learning from pretrained models, hyperparameter tuning, pruning of redundant parameters, quantization for reduced memory usage, and ensemble learning for improved robustness. These techniques not only improve the diagnostic accuracy of models but also reduce latency and enable real-time inference on devices such as smartphones, Raspberry Pi, or specialized AI accelerators. The integration of optimized ML models into healthcare has the potential to revolutionize skin disease detection. Such systems can provide early screening, remote diagnosis, and decision support for dermatologists, ultimately increasing accessibility and reducing the burden on healthcare systems. Furthermore, optimized deployment ensures that automated skin disease detection is feasible even in low-resource environments, paving the way for scalable and equitable healthcare solutions.

II. LITERATURE REVIEW

Esteva et al. (2017) demonstrated that AI could match expert dermatologists in identifying over 2,000 skin conditions using a massive dataset of clinical-quality images. The study highlighted the potential for scalable, mobile-based diagnosis, albeit noting limitations in translating to cellphone-quality imagery. **Velasco et al. (2019)** implemented a MobileNet-based model on Android. Utilizing transfer learning and techniques like oversampling and data augmentation, they achieved up to **94.4% accuracy** on seven skin disease classes. **Yilmaz et al. (2021)** benchmarked lightweight architectures (including MobileNet variants) on the ISIC 2017 dataset. The best model—NASNetMobile—reached an accuracy of **82%**, demonstrating feasibility of mobile-ready models for cancer detection. **Yao et al. (2021)** addressed small, imbalanced datasets by using moderate-complexity CNNs with dropout, innovative augmentations (Modified RandAugment), and a novel Multi-Weighted New Loss (MWNL). Their strategy yielded classification performance comparable to ensemble methods while being computationally lightweight and mobile-ready. **Goceri (2021)** optimized a MobileNet-based lightweight network with a hybrid loss function for mobile diagnosis of common skin ailments (like acne and psoriasis), emphasizing real-time inference on constrained devices. **Shrivastava et al. (2023)** created a lightweight model tailored for NVIDIA Jetson Nano. Using transfer learning with ResNet50 and MobileNet, they achieved up to **93.3% accuracy** on the PH2 dataset, underscoring edge feasibility. A 2023 study in *Advanced Intelligent Systems* describes how TensorFlow Lite (TFLite) along with Android tools like Kotlin and CameraX enable real-time skin lesion detection on smartphones, emphasizing local inference for speed and privacy. **Srinivasu et al. (2021)** developed a hybrid **MobileNetV2 + LSTM** model using the HAM10000 dataset, achieving over **85% accuracy** while halving computational load compared to conventional MobileNet. A mobile app implementation further demonstrates applicability in low-resource healthcare settings.

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An ensemble-based approach using **federated learning** enables models at edge (e.g., smart dermoscopy) to update and improve a global cloud model while minimizing data transmission via gradient compression. This enhances adaptability and privacy. A systematic review in *MDPI Processes (2023)* analyzed ML methods across skin lesion detection, underscoring challenges like dataset imbalance and variability, and highlighting the importance of preprocessing and traditional and deep learning approaches for segmentation and classification.

III. METHODOLOGY

The diagnosis of new skin cancer cases keeps rising at global health levels annually. The successful treatment of this disease depends on detecting it early and performing correct diagnostic assessments. The traditional method for dermatologists to detect suspicious skin growths depends solely on visual examination. The ability of skilled dermatologists to achieve accurate diagnosis stands high yet visual assessments remain time-consuming and require manual labor and display human-related variability because of both individual performance and professional experience. Outcomes become inconsistent because medical professionals do not have the same access to specialized care in regions where health care specialization is limited [4]. This paper works towards creating an automated skin disease detection system through the implementation of cutting-edge deep learning methods. The proposed system enhances diagnostic precision through VGG19 CNNs and Grad-CAM interpretability tools for visual explanation purposes in supporting clinical decisions. Dermatologists receive assistance from this system which functions as a diagnostic tool to lower both their diagnostic errors and practice workload. These AI-powered medical resources become important for remote healthcare settings since they expand professionally advanced analysis functions across underserved regions. The base model used for feature extraction is a pretrained (on ImageNet) VGG-19 convolutional neural network. VGG-19 holds the distinction of being renowned for its deep architecture and powerful feature extraction capabilities, making it especially well-suited to capture the fine details and textures in images of skin lesions. It is essentially first trained or pre-trained on ImageNet (that is, on general data) and then, only then, fine-tuned on the skin lesion so that the model is similar for classification. Finally, by applying 'fine-tuning' technique to pretrained VGG19 model which will allow us to retrain some of the top layers of our model whilst repurposing those layers to the feature learning task. Our approach is based on transfer learning paradigm and thus is able to learn skin disease classification with low computational resources and minimal training time. The initial stage of constructing a high-performing deep learning model for the categorization of skin maladies involves obtaining a quality dataset. Substantial and diverse datasets comprising accurately labeled images of skin lesions, like ISIC Archive and DermNet, will serve as outstanding data sources to train a strong model. The datasets should comprise images of different types of skin conditions taken under various lighting conditions and on different types of skin so that they may be wellbalanced datasets representing real life. Image preprocessing improves the quality of input data[5]. The images should be resized to the same size, usually 224x224 pixels, for consistency in the dataset and to aid deep learning models in processing. Pixel values should also be normalized to some fixed value, like between 0-1, to make input distributions similar and help with faster model convergence normalized values also help reduce the effect of different images having different brightness and contrast levels.

IV. CONCLUSION

Enhancing skin disease detection with optimized machine learning models offers a transformative approach to dermatological care, bridging the gap between advanced AI technologies and accessible healthcare delivery. While traditional deep learning models have demonstrated high accuracy, their computational requirements often limit their use in real-world, resource-constrained settings. The literature and experimental evidence highlight that through optimization techniques—including transfer learning, hyperparameter tuning, pruning, quantization, and ensemble learning—ML models can achieve both high diagnostic accuracy and computational efficiency. Optimized models not only reduce latency and memory footprint but also enable real-time inference on mobile and edge devices, making them suitable for deployment in teledermatology applications and low-resource environments. Furthermore, such systems enhance early detection of conditions like melanoma, where timely intervention is critical, thereby potentially saving lives. Despite these advances, challenges remain in addressing dataset imbalance, generalization across diverse skin types, and ensuring explainability and trustworthiness of AI systems in clinical practice. Future work should emphasize the integration of federated learning, explainable AI (XAI), and robust clinical validation to improve fairness, transparency, and adoption by healthcare professionals.

REFERENCES

1. Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). *Dermatologist-level classification of skin cancer with deep neural networks*. Nature, 542(7639), 115–118. https://doi.org/10.1038/nature21056
2. Brinker, T. J., Hekler, A., Enk, A. H., Klode, J., Hauschild, A., Berking, C., … & von Kalle, C. (2019). *Deep learning outperformed 136 of 157 dermatologists in a head-to-head dermoscopic melanoma image classification task*. European Journal of Cancer, 113, 47–54. https://doi.org/10.1016/j.ejca.2019.04.001
3. Tschandl, P., Rinner, C., Apalla, Z., Argenziano, G., Codella, N., Halpern, A., … & Kittler, H. (2020). *Human–computer collaboration for skin cancer recognition*. Nature Medicine, 26(8), 1229–1234. https://doi.org/10.1038/s41591-020-0942-0
4. Mahbod, A., Schaefer, G., Wang, C., Ecker, R., & Ellinger, I. (2019). *Transfer learning using a multi-scale and multi-network ensemble for skin lesion classification*. Computer Methods and Programs in Biomedicine, 186, 105241. https://doi.org/10.1016/j.cmpb.2019.105241
5. Hasan, M. K., Al Shamshirband, S., Yee, L. Y., & Alazab, M. (2020). *Machine learning-based skin disease diagnosis: A comprehensive review*. Healthcare, 8(3), 236. https://doi.org/10.3390/healthcare8030236
6. Albahar, M. A. (2019). *Skin lesion classification using convolutional neural network with novel regularizer*. IEEE Access, 7, 38306–38313. https://doi.org/10.1109/ACCESS.2019.2906359
7. Han, S. S., Kim, M. S., Lim, W., Park, G. H., Park, I., & Chang, S. E. (2018). *Classification of the clinical images for benign and malignant cutaneous tumors using a deep learning algorithm*. Journal

of Investigative Dermatology, 138(7), 1529–1538. https://doi.org/10.1016/j.jid.2018.01.028

8. Pham, T. C., Luong, C. M., Hoang, V. D., & Doucet, A. (2021). *Improving skin disease classification by combining deep learning features and clinical criteria*. Computers in Biology and Medicine, 134, 104458. https://doi.org/10.1016/j.compbiomed.2021.104458
9. Bassi, P. R., & Attux, R. (2022). *Skin disease classification using deep learning: A systematic review*. IEEE Access, 10, 122493–122509. https://doi.org/10.1109/ACCESS.2022.3223182
10. Codella, N. C., Rotemberg, V., Tschandl, P., Celebi, M. E., Dusza, S. W., Gutman, D., … & Halpern, A. (2019). *Skin lesion analysis toward melanoma detection 2018: A challenge hosted by the International Skin Imaging Collaboration (ISIC)*. arXiv preprint arXiv:1902.03368.