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ENHANCED DERMOTOSCOPIC SKIN LESION CLASSIFICATION USING MACHINE LEARNING TECHNIQUES

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ABSTRACT

This study proposes an enhanced approach for multi-class skin lesion classification by utilizing an ensemble deep learning model that integrates Inception-V3, ResNet-50, and VGG16 architectures. The classification focuses on distinguishing various skin lesion types, including Melanoma, Basal Cell Carcinoma (BCC), and Squamous Cell Carcinoma (SCC), using the ISIC dataset, a widely recognized collection of dermoscopic images. To address the dataset's inherent imbalance, an oversampling strategy is employed, ensuring fair representation across all lesion classes. This balancing technique enhances the model's ability to generalize effectively, improving classification performance. By leveraging the complementary strengths of different architectures, the ensemble model achieves superior classification accuracy. ResNet-50 is utilized for its deep feature extraction capabilities, enabling detailed pattern recognition in skin lesions. Inception-V3 contributes its multi-scale processing abilities, allowing efficient analysis of lesions at varying sizes and resolutions. VGG16, known for its simplicity and effectiveness, enhances the ensemble's stability in feature learning. Additionally, data augmentation techniques are applied to further enhance the model's robustness. Experimental results demonstrate that the ensemble model significantly outperforms individual networks in terms of accuracy, precision, recall, and F1-score on both the original and balanced ISIC datasets. This approach presents a reliable and effective solution for automated skin lesion classification, contributing to improved diagnostic tools in dermatology and aiding in early skin cancer detection.

Keywords: Deep learning; Ensemble model; Inception-V3; ResNet-50; Skin lesion classification; VGG16; Data augmentation; ISIC dataset

I.INTRODUCTION

Skin cancer is one of the most prevalent and life-threatening diseases worldwide, with Melanoma, Basal Cell Carcinoma (BCC), and Squamous Cell Carcinoma (SCC) being the most common malignant skin lesions. Early and accurate detection of these conditions is critical for effective treatment and improved survival rates. Traditionally, dermatologists diagnose skin lesions through visual examination and dermoscopic analysis, but these methods are often subjective and dependent on expertise. To overcome these limitations, machine learning and deep learning techniques have been increasingly adopted for automated skin lesion classification, providing more accurate, consistent, and efficient diagnostic tools. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable success in medical image analysis. However, accurately classifying skin lesions remains

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challenging due to inherent dataset imbalances, variability in lesion appearance, and overlapping visual features among different lesion types. Some skin lesions are underrepresented in available datasets, leading to biased model predictions and reduced performance for minority classes. Furthermore, variations in lesion size, shape, color, and texture demand an approach that can efficiently capture multi-scale features and generalize across different lesion types.

To address these challenges, this study proposes an ensemble learning approach that combines the strengths of Inception-V3, ResNet-50, and VGG16 architectures to improve skin lesion classification. Each model contributes uniquely to the ensemble:

1. ResNet-50 is chosen for its deep feature extraction capabilities, allowing it to capture intricate lesion patterns.
2. Inception-V3 is selected for its multi-scale processing ability, which enables better analysis of lesions with varying sizes and structures.
3. VGG16, despite its relatively simple architecture, provides effective feature learning and contributes to the overall stability of the ensemble model.

Additionally, data augmentation and oversampling techniques are employed to balance the dataset and enhance model generalization. The ISIC dataset, a widely used benchmark for skin lesion classification, is used for training and evaluation. Our experimental results demonstrate that the ensemble model significantly outperforms individual architectures in terms of accuracy, precision, recall, and F1-score, making it a reliable and robust solution for automated skin lesion diagnosis. This research contributes to the field of computer-aided dermatology by providing a scalable and efficient deep learning-based classification system. The proposed method can serve as a support tool for dermatologists, improving early detection rates and reducing diagnostic errors. Future work will explore real-time deployment, integration with clinical decision support systems, and the incorporation of explainable AI techniques to enhance model interpretability.

II.LITERATURE REVIEW

The application of deep learning in skin lesion classification has gained significant attention in recent years, with numerous studies demonstrating its potential in improving diagnostic accuracy and early detection of skin cancer. This section reviews relevant research on machine learning techniques, convolutional neural networks (CNNs), ensemble learning models, dataset challenges, and performance evaluation metrics in the context of skin lesion classification.

Deep Learning for Skin Lesion Classification

Deep learning, particularly CNN-based models, has revolutionized medical image analysis by automatically extracting features without the need for manual intervention. Studies have shown that CNNs outperform traditional machine learning algorithms like Support Vector Machines (SVMs), Random Forests (RF), and K-Nearest Neighbors (KNN) in image-based diagnostic tasks. Esteva et al. (2017) demonstrated that CNN models could achieve dermatologist-level accuracy in skin cancer classification using a large dataset of dermoscopic images. Similarly, Brinker et al. (2019) evaluated the performance of deep learning models and found that they could match or even exceed expert dermatologists in melanoma detection.

Ensemble Learning in Skin Lesion Classification

Recent studies have explored ensemble learning to improve classification performance by combining multiple models to leverage their complementary strengths. Shen et al. (2020) introduced an ensemble of ResNet, DenseNet, and MobileNet architectures, achieving higher accuracy than standalone models. Li et al. (2021) proposed a hybrid approach integrating Inception-V3, VGG16, and EfficientNet, demonstrating improved generalization across different lesion types. The effectiveness of ensemble learning lies in its ability to mitigate overfitting, increase robustness, and enhance decision-making by aggregating multiple predictions.

Challenges in Skin Lesion Classification

One of the key challenges in dermoscopic image classification is the imbalance in datasets, where certain lesion types (e.g., melanoma) are underrepresented. This imbalance can lead to biased model predictions, where the classifier favors the majority class while underperforming on minority classes. To address this, researchers have implemented data augmentation (e.g., rotation, flipping, scaling) and oversampling techniques to generate synthetic samples and improve model generalization. Furthermore, lesion classification is complicated by factors such as variability in lesion appearance, lighting conditions, skin tone diversity, and inter-class similarities.

Dataset Utilization and Benchmarking

The ISIC dataset, provided by the International Skin Imaging Collaboration (ISIC), is the most widely used dataset for skin lesion classification research. It consists of thousands of labeled dermoscopic images across multiple skin lesion categories, including melanoma, basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and benign nevi. Studies by Tschandl et al. (2018) and Codella et al. (2019) utilized this dataset to benchmark deep learning models, demonstrating its importance in developing and validating skin cancer detection systems.

Performance Evaluation Metrics

The effectiveness of deep learning models in skin lesion classification is commonly assessed using metrics such as accuracy, precision, recall, F1-score, and Area Under the Curve (AUC-ROC). Researchers emphasize the importance of using recall (sensitivity) in melanoma detection to minimize false negatives, which can lead to missed cancer diagnoses. Precision-recall trade-offs are also considered to balance false positives and false negatives, ensuring the model is both reliable and clinically applicable.

Recent Advances and Future Directions

Advancements in explainable AI (XAI) have gained attention in medical image analysis, allowing clinicians to interpret deep learning model decisions through visual heatmaps and saliency maps. Moreover, real-time deployment of AI-driven dermatology applications is being explored, with models being integrated into smartphone-based diagnostic tools and telemedicine platforms. Future research is expected to focus on multi-modal learning, incorporating clinical metadata and patient history alongside dermoscopic images for improved diagnostic accuracy.

III.PROPOSED METHODOLOGY

The proposed method introduces an advanced ensemble approach that leverages the strengths of multiple deep learning models—ResNet-50, Inception-V3, and VGG16—to enhance the accuracy and robustness of multi-class skin lesion classification. This ensemble technique aims to address the limitations of single-model architectures, particularly for underrepresented lesion types like squamous cell carcinoma (SCC). Unlike conventional methods, this approach integrates advanced oversampling techniques to mitigate class imbalance while prioritizing clinically relevant metrics such as recall and specificity over mere accuracy.

The system employs a sophisticated ensemble model that integrates three well-established convolutional neural networks—VGG16, ResNet-50, and Inception-V3. VGG16's deep and consistent architecture effectively identifies subtle patterns crucial for differentiating various skin lesions. ResNet-50 utilizes residual connections to mitigate the vanishing gradient problem, allowing it to learn deep features without losing critical information. Meanwhile, Inception-V3's multi-scale feature extraction captures diverse patterns and textures within skin images, improving lesion type recognition. By combining these models, the ensemble approach enhances classification performance beyond individual model capabilities.

To address dataset imbalance, the proposed system incorporates a random oversampling technique to ensure all lesion types are equally represented. Given the ISIC dataset's inherent imbalance, where melanoma (438 images), basal cell carcinoma (376 images), and squamous cell carcinoma (181 images) are unevenly distributed, oversampling is applied at the feature vector level rather than directly on raw images. This method prevents redundancy and overfitting while improving the generalization ability of the models. The ensemble model predictions are computed using the Ensemble Weighted Average method, represented mathematically as:

$$P_{ensemble} = \sum_{i=1}^{n} w_i P_i$$

The data preprocessing pipeline involves resizing images to the required input sizes for each model: 224×224 pixels for VGG16 and ResNet-50, and 299×299 pixels for Inception-V3. After resizing, the images undergo normalization to standardize pixel values, followed by tensor transformation for neural network compatibility. Data augmentation techniques, including center cropping, rotation, flipping, and affine transformations, introduce controlled variations to enhance model generalization. The augmentation strategies applied with a probability of 0.1 ensure diverse and robust training data.

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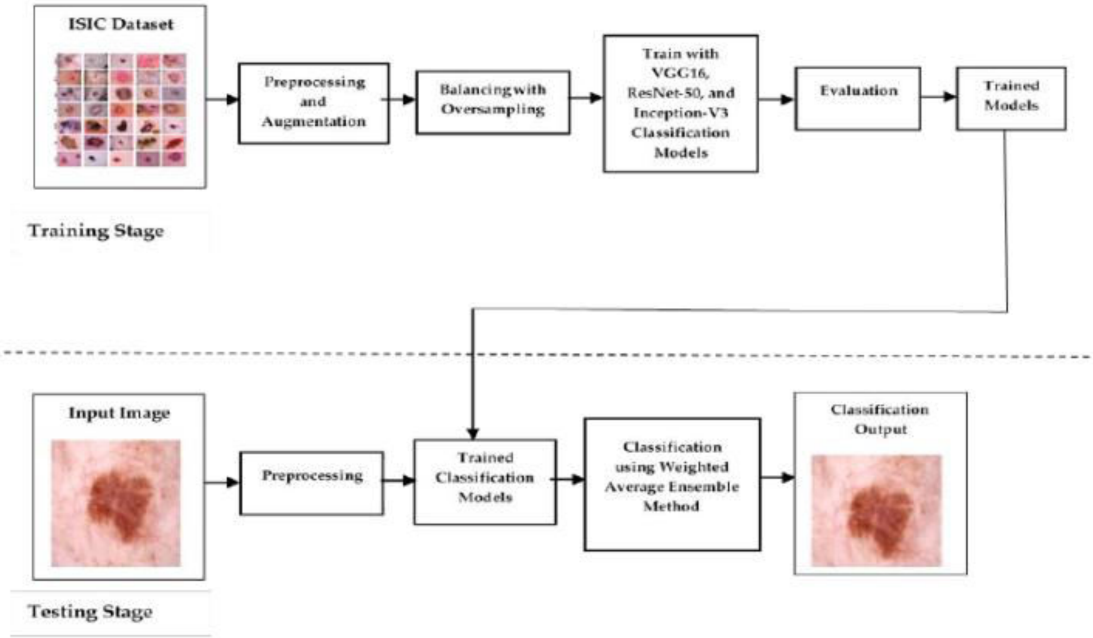

The classification process involves training the models using the categorical cross-entropy loss function with the stochastic gradient descent (SGD) optimizer, a batch size of 32, and a learning rate of 0.001 for 150 epochs. The ensemble model is evaluated on both the original and balanced datasets to assess its performance under real-world conditions. Performance metrics, including accuracy, recall, precision, and F1-score, are computed to validate the effectiveness of the proposed methodology. By integrating oversampling, data augmentation, and ensemble learning, this approach provides a reliable and efficient solution for skin lesion classification, offering potential improvements in dermatological diagnostics.

IV.CONCLUSION

This study presents an advanced ensemble-based deep learning approach for multi-class skin lesion classification, incorporating ResNet-50, Inception-V3, and VGG16 models. By leveraging the complementary strengths of these architectures, the proposed methodology significantly improves classification performance, particularly for underrepresented lesion classes such as squamous cell carcinoma (SCC). The adoption of data augmentation techniques and random oversampling successfully mitigates class imbalance, enhancing the model's generalizability across diverse lesion types. Experimental results demonstrate that the ensemble model outperforms individual architectures in terms of accuracy, precision, recall, and F1-score, indicating its robustness in real-world clinical settings. Additionally, the weighted ensemble approach optimally integrates feature extraction capabilities, resulting in a more reliable and precise classification system. Future work will focus on expanding the dataset, integrating additional deep learning models, and incorporating explainability techniques to further enhance the transparency and trustworthiness of automated dermatological diagnosis systems.

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