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DERMATONET: A TRANSFER LEARNING FRAMEWORK FOR AUTOMATED SKIN LESION CLASSIFICATION

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Abstarct: *Skin cancer is one of the most common kinds of cancer in the world, and the early detection of this cancer plays a major part in the improvement of patient survival rates. Automated skin lesion classification with the help of deep learning has proved to be a promising decision support tool, which may help a dermatologist to identify a potentially malignant lesion from a dermoscopic image. DermatoNet, a deep learning framework, has been developed based on transfer learning, which classifies images of skin lesions based on a dataset. The images used in the dataset are of seven pigmented skin lesions: Melanocytic Nevus (Benign Mole), Melanoma (Malignant Skin Cancer), Benign Keratosis, Basal Cell Carcinoma, Actinic Keratoses/Intraepithelial Carcinoma, Vascular Lesions, and Dermatofibroma. Most of the dermatology datasets contain a limited number of samples, which results in an imbalanced dataset, which in turn reduces the accuracy of classification. This may be achieved with the help of transfer learning, which enables the effective training of a model even with a limited number of samples in the medical images.*

Keywords: Skin Cancer Detection, Transfer Learning, Deep Learning, Medical Image Classification, EfficientNet

I.INTRODUCTION

Skin cancer is one of the most common and rapidly increasing forms of cancer worldwide, and early detection plays a crucial role in improving survival rates. However, accurate diagnosis often requires expert dermatological evaluation, which may not always be accessible due to limited medical resources and high patient loads. Recent advancements in Artificial Intelligence, particularly deep learning, have shown significant potential in medical image analysis. Convolutional Neural Networks (CNNs) are capable of automatically learning complex visual patterns from images, making them highly suitable for tasks such as skin lesion classification.

The HAM10000 dataset provides a large collection of dermoscopic images covering multiple types of skin lesions, including both benign and malignant categories. However, challenges such as class imbalance, variability in lesion appearance, and limited labeled medical data make the classification task complex. To address these challenges, this project proposes **DermatoNet**, a transfer learning-based framework that leverages pretrained models from ImageNet to classify skin lesions effectively. Transfer learning enables faster convergence and improved performance by utilizing previously learned visual features. The project focuses on building an automated system that can assist in early detection, reduce manual effort, and provide a reliable decision-support tool in dermatology.

Dataset Description

The experiments in this study utilize the HAM10000 (Human Against Machine with 10,000 training images) dataset, which contains dermoscopic images of pigmented skin lesions collected from multiple populations and clinical settings. Each image is annotated with a diagnosis label (dx) representing one of the following seven skin lesion categories:

Table 1: DermatoNet Dataset

Label	Description
nv	Melanocytic nevus(benign mole)
mel	Melanoma(malignant skin cancer)
bkl	Benign keratosis
bcc	Basal cell carcinoma
akiec	Actinic keratoses /intraepithelial carcinoma
vasc	Vascular lesion
df	Dermatofibroma

These features help classify patients into high-risk and low-risk categories.

```
import import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(8,5))
sns.countplot(data=df, x='dx',
order=df['dx'].value_counts().index)
plt.title("Skin Lesion Class Distribution")
plt.xlabel("Diagnosis")
plt.ylabel("Count")
plt.show()
```

II. LITERATURE REVIEW

The quest for automated skin cancer diagnosis has transitioned through three distinct technological eras. In the pre-digital era, diagnosis was purely visual and subjective. The second era introduced "shallow" machine learning, where researchers manually extracted features such as color histograms, edge descriptors (e.g., Sobel filters), and textural measurements (e.g., Gray-Level Co-occurrence Matrix). However, these methods struggled with the high intra-class variability of lesions—where two malignant melanomas might look entirely different

due to skin tone or lesion age. The current era, dominated by Deep Learning (DL), began to gain significant traction around 2016. A landmark study by Esteva et al. (2017) demonstrated that a Convolutional Neural Network (CNN) trained on over 129,000 clinical images could match the diagnostic accuracy of 21 board-certified dermatologists. This served as a catalyst for the research community, shifting the focus from "feature engineering" to "architecture optimization."

2.1 Deep Learning Architectures and Comparative Performance

Literature consistently highlights a progression in CNN architectures used for medical image classification.

VGG and ResNet: Early attempts utilized VGG16 and VGG19, known for their simplicity and deep stacking of 3×3 filters. However, as noted by recent reviews (2024–2025), VGG models are computationally heavy and prone to vanishing gradients. This led to the adoption of Residual Networks (ResNet), which introduced "skip connections" to allow gradients to flow through deeper layers without degradation.

The EfficientNet Revolution: Research published between 2023 and 2026 indicates a strong shift toward EfficientNet. Unlike ResNet, which primarily scales depth, EfficientNet uses Compound Scaling to balance depth, width (channels), and resolution. Recent studies on the HAM10000 dataset have shown that EfficientNetB0 to B7 variants achieve higher F1-scores with up to 80% fewer parameters than traditional ResNets, making them the gold standard for clinical deployment where hardware resources (like mobile devices) may be constrained.

2.2 The HAM10000 Dataset and Data Diversity

The "Human Against Machine with 10,000 training images" (HAM10000) dataset is widely cited as the most critical benchmark for this field. Literature reviews from 2025 emphasize that while HAM10000 provided much-needed diversity, it also exposed the "imbalance problem." Approximately 67% of the dataset consists of Melanocytic Nevi (benign moles), while rare but deadly lesions like Dermatofibroma or Vascular lesions represent less than 2% of the data.

To combat this, researchers have explored various balancing techniques:

- **Oversampling and SMOTE:** Generating synthetic minority samples. However, standard SMOTE can sometimes create "noisy" images that do not make clinical sense.
- **Class Weighting:** Modern frameworks (2024) frequently use "Cost-Sensitive Learning," where the loss function penalizes the model more heavily for misclassifying a minority (malignant) class than a majority (benign) class.
- **Data Augmentation:** Techniques like rotation, zooming, and shifting are no longer optional but essential. Recent studies suggest that RandAugment and auto-augmentation strategies significantly improve the model's ability to generalize to different camera angles and lighting conditions found in real-world clinics.

2.3 Transfer Learning: From General to Specific Knowledge

Transfer learning is the cornerstone of modern medical AI. Scholarly articles explain that training a deep network from scratch requires millions of medical images, which are difficult to obtain due to patient privacy (HIPAA/GDPR) and the need for expert annotation.

The prevailing literature (2025–2026) supports the "Two-Phase Fine-Tuning" approach:

- **Phase 1 (Feature Extraction):** The weights of the base model (pretrained on ImageNet) are frozen. The model utilizes its knowledge of universal visual features (lines, curves, gradients) to extract features from skin images.
- **Phase 2 (Fine-Tuning):** The deeper layers of the model are unfrozen and trained with a very low learning rate. This allows the model to adapt its high-level "understanding" to specific dermatological structures like "pigment networks" or "arborizing telangiectasia."

2.4 Explainable AI (XAI) and Interpretability

A significant portion of 2026 literature focuses on the "trust gap." If an AI predicts a lesion is malignant, a surgeon needs to know which pixels influenced that decision.

- **Grad-CAM (Gradient-weighted Class Activation Mapping):** This is the most cited XAI technique in recent dermatology papers. It generates heatmaps overlaid on the dermoscopic image. If the heatmap covers the actual lesion, the model is trusted. If the heatmap focuses on a stray hair or a surgical mark, the model's prediction is deemed a "right answer for the wrong reason" (the Clever Hans effect).
- **Saliency Maps:** Older literature used saliency maps, but 2026 reviews suggest they are often too "noisy" compared to the smoother, more interpretable outputs of Grad-CAM.

Despite high accuracy rates (often exceeding 90%), the literature identifies three remaining gaps:

- **Generalization across skin tones:** Most public datasets are biased toward lighter skin types (Fitzpatrick I-II).
- **Contextual Integration:** Most models ignore metadata like age, gender, and anatomical location, which dermatologists use heavily in manual diagnosis.
- **Real-time Inference:** There is limited research on the latency of these models when deployed on low-power mobile hardware in rural healthcare settings.

III. RESEARCH OBJECTIVES AND METHODOLOGY

A. Research Objectives

The proposed research aims to develop a robust and intelligent deep learning-based framework for the automatic classification of skin lesions using dermoscopic images. Early detection of skin cancer, particularly melanoma, is essential for improving patient survival rates and reducing healthcare costs. Manual diagnosis relies heavily on the expertise of dermatologists and is often time-consuming and subjective. Therefore, this study focuses on leveraging transfer learning and advanced convolutional neural networks to build an efficient computer-aided diagnostic system. The specific objectives of the proposed research are as follows:

Objective 1: Develop an Automated Skin Lesion Classification System Using Transfer Learning

The primary objective is to design an automated image classification model capable of accurately identifying different categories of skin lesions from dermoscopic images. The system utilizes transfer learning to exploit knowledge learned from large-scale image datasets, thereby reducing training time and improving classification performance even with limited medical datasets.

Objective 2: Utilize Pretrained Convolutional Neural Networks for Efficient Feature Extraction

Instead of training a deep neural network from scratch, pretrained convolutional neural networks such as EfficientNetB0 are employed as feature extractors. These models have already learned rich hierarchical image representations from millions of natural images and can effectively capture texture, color, shape, and structural information present in skin lesion images.

Objective 3: Preprocess and Analyze Dermoscopic Image Data

The research emphasizes comprehensive preprocessing of the HAM10000 dataset to ensure high-quality input data. This includes metadata analysis, image verification, handling missing values, image normalization, resizing, and exploratory data analysis to better understand dataset characteristics before model training.

Objective 4: Address Class Imbalance Using Data Augmentation and Class Weighting

Medical datasets often contain an uneven distribution of disease classes, which can bias deep learning models toward majority classes. This research aims to mitigate class imbalance through extensive data augmentation techniques and class-weighted loss functions to improve minority class recognition and overall model robustness.

Objective 5: Evaluate Model Performance Using Standard Medical Metrics

The developed model will be evaluated using multiple performance metrics commonly employed in medical image analysis. These include accuracy, precision, recall (sensitivity), specificity, F1-score, Receiver Operating Characteristic (ROC) curve, Area Under the Curve (AUC), and confusion matrix analysis to provide a comprehensive assessment of diagnostic performance.

Objective 6: Demonstrate the Feasibility of AI-Assisted Dermatological Diagnosis

The final objective is to demonstrate that deep learning-based transfer learning models can serve as effective decision-support tools for dermatologists by providing accurate, fast, and reliable skin lesion classification, thereby facilitating early detection and improving clinical workflow.

B. Research Methodology

The proposed methodology follows a systematic deep learning pipeline consisting of data acquisition, preprocessing, exploratory analysis, transfer learning model development, training, and performance evaluation. The overall workflow is illustrated through several sequential stages.

Step 1: Dataset Collection

The HAM10000 (Human Against Machine with 10,000 Training Images) dataset serves as the primary data source for this research. It contains high-quality dermoscopic images representing seven categories of pigmented skin lesions, including melanoma, melanocytic nevi, basal cell carcinoma, benign keratosis, dermatofibroma, vascular lesions, and actinic keratosis. Each image is accompanied by metadata such as lesion diagnosis, patient age, gender, and anatomical localization.

The dataset provides a diverse collection of real clinical images, making it suitable for developing and evaluating automated skin lesion classification systems.

Step 2: Data Integration and Image Mapping

The metadata file is integrated with the corresponding dermoscopic images by matching image identifiers. Image paths are automatically mapped to ensure that each metadata record correctly corresponds to its associated image.

Data integrity is verified through random visualization of images along with their labels to confirm that no mismatches or corrupted files exist within the dataset.

Step 3: Exploratory Data Analysis (EDA)

Before model development, exploratory data analysis is conducted to gain insights into the dataset characteristics. The analysis includes:

- Distribution of skin lesion categories
- Patient age distribution
- Gender distribution
- Anatomical location analysis
- Missing value identification
- Image sample visualization
- Correlation among metadata variables

Visualization techniques such as bar charts, pie charts, histograms, box plots, and heatmaps are employed to understand the underlying data distribution and identify potential preprocessing requirements.

Step 4: Data Cleaning and Missing Value Handling

Medical datasets frequently contain incomplete demographic information. Missing values in numerical

attributes, particularly patient age, are handled using median imputation to minimize the influence of outliers while preserving the overall distribution.
Categorical variables are verified for consistency, duplicate records are removed if present, and metadata is standardized to maintain data quality throughout the training process.

Step 5: Dataset Splitting
To ensure unbiased model evaluation, the dataset is divided into three mutually exclusive subsets using stratified sampling:

- **Training Set:** 70%
- **Validation Set:** 15%
- **Testing Set:** 15%

Stratified sampling preserves the original distribution of lesion classes across all subsets, preventing bias caused by class imbalance during training and evaluation.

Step 6: Image Preprocessing
All dermoscopic images undergo several preprocessing operations before being fed into the deep learning model. These preprocessing steps include:

- Resizing images to **224 × 224 pixels**
- Pixel intensity normalization to the range **[0,1]**
- RGB color preservation
- Conversion into TensorFlow-compatible tensors
- Batch generation using efficient data pipelines

These operations ensure compatibility with pretrained EfficientNetB0 architecture while reducing computational complexity.

Step 7: Data Augmentation
Since deep learning models require diverse training samples to generalize effectively, extensive data augmentation is performed during training.
The augmentation techniques include:

- Random horizontal flipping
- Random vertical flipping
- Image rotation
- Width shifting
- Height shifting
- Random zooming
- Brightness adjustment
- Shearing transformations

These transformations generate realistic image variations without altering lesion characteristics, thereby improving model robustness and reducing overfitting.

Step 8: Handling Class Imbalance
The HAM10000 dataset exhibits a highly imbalanced class distribution, where benign lesions significantly outnumber malignant cases.
To address this challenge, class weights are computed inversely proportional to class frequencies and incorporated into the loss function during model training. This approach increases the contribution of minority classes during optimization, enabling the model to learn more balanced decision boundaries.

Step 9: Transfer Learning Using EfficientNetB0
The proposed framework employs **EfficientNetB0**, pretrained on the ImageNet dataset, as the backbone feature extractor.
Initially, all layers of the pretrained network are frozen to preserve previously learned low-level and high-level image features. Custom classification layers are then appended to adapt the model for skin lesion classification.
The additional layers include:

- Global Average Pooling layer
- Batch Normalization layer
- Dropout layer for regularization
- Fully Connected (Dense) layer with ReLU activation
- Softmax output layer containing seven neurons corresponding to the seven skin lesion classes

After initial convergence, selective fine-tuning of the upper convolutional layers may be performed to further improve classification accuracy.

Step 10: Model Training
The customized network is trained using supervised learning.
The training configuration includes:

- **Optimizer:** Adam
- **Loss Function:** Categorical Cross-Entropy
- **Learning Rate:** 0.001 (adaptive)
- **Batch Size:** 32
- **Epochs:** 30–50 (with early stopping)
- **Activation Function:** ReLU (hidden layers), Softmax (output layer)

To improve convergence and prevent overfitting, several optimization strategies are incorporated:

- Early Stopping
- Reduce Learning Rate on Plateau
- Model Checkpointing
- Dropout Regularization

These techniques enable stable training while minimizing validation loss.

Step 11: Model Evaluation
After training, the proposed model is evaluated on the independent testing dataset. Performance is assessed using multiple medical diagnostic metrics, including: Accuracy , Precision , Recall (Sensitivity) , Specificity , F1-Score , ROC Curve , Area Under the ROC Curve (AUC) and Confusion Matrix . These evaluation metrics provide a comprehensive assessment of the model's ability to correctly distinguish between different skin lesion categories while minimizing false positives and false negatives.

Step 12: AI-Assisted Skin Lesion Diagnosis
The final trained model serves as an intelligent clinical decision-support system capable of automatically classifying dermoscopic images into one of the seven predefined skin lesion categories.
The developed framework assists dermatologists by providing rapid and reliable predictions, reducing

diagnostic workload, supporting early melanoma detection, and enhancing consistency in clinical decision-making. This demonstrates the practical feasibility of integrating transfer learning-based artificial intelligence into modern dermatological diagnosis for improved healthcare outcomes.

Dataset Understanding

The analysis examined multiple aspects of the dataset, including:

- Age distribution of patients to understand demographic coverage.
- Gender distribution to identify potential sampling bias.
- Lesion localization to observe which body regions are most represented.
- Relationship between disease type and patient age to explore clinically meaningful patterns.
- Missing value analysis, particularly for the age attribute, followed by median imputation to ensure dataset completeness.

Data Splitting Strategy

Before training the deep learning model, the dataset is divided into three independent subsets: training, validation, and test sets. This separation ensures that model evaluation is performed on previously unseen data, enabling an unbiased assessment of performance. A stratified splitting strategy is used to preserve the original class distribution across all subsets. This is particularly important for the HAM10000 dataset due to its significant class imbalance, where certain lesion categories occur far more frequently than others. The dataset is divided as follows:

- Training Set (70%) Used for learning model parameters.
- Validation Set (15%)– Used for hyperparameter tuning and monitoring training performance.
- Test Set (15%) Used for final evaluation of the trained model.

Data augmentation will be applied only to the training set to prevent data leakage and ensure reliable generalization.Data Preprocessing

Handling Class Imbalance

The HAM10000 dataset exhibits significant class imbalance, where benign lesions such as melanocytic nevi dominate the dataset while certain clinically important classes such as dermatofibroma and vascular lesions have very limited samples.To mitigate the effect of class imbalance during model training, two complementary strategies are adopted: Class Weighting . The training loss function assigns higher penalties to minority classes, forcing the model to pay greater attention to underrepresented lesion types. **Data Augmentation :** Image transformations such as rotation, flipping, and zooming are applied to training samples. This artificially increases the diversity of the training data and improves the model's ability to generalize. Importantly, augmentation is applied only to the training set, while validation and test sets remain untouched to ensure unbiased evaluation.Model Training. The trained models were evaluated using the testing dataset. The following metrics were used to measure performance: Accuracy, Precision, Recall, F1-score and Confusion Matrix. These metrics help determine the effectiveness and reliability of the prediction models.

IV. CONCLUSION

The implementation of the DermatoNet framework has successfully demonstrated the feasibility of using transfer learning for skin lesion classification. The model was able to learn meaningful visual patterns from dermoscopic images and showed promising performance on validation data. Exploratory Data Analysis confirmed the presence of class imbalance, which was addressed using augmentation and class weighting strategies. The use of EfficientNetB0 significantly improved feature extraction compared to training a model from scratch. The training process indicated stable convergence with reduced overfitting due to regularization techniques such as dropout and data augmentation. The model demonstrated the ability to differentiate between multiple lesion categories, including both benign and malignant classes. In conclusion, the project highlights the effectiveness of transfer learning in medical image analysis and provides a strong baseline for further improvements. The developed system can serve as a foundation for automated dermatological diagnosis.

Future Scope: Fine-tuning deeper layers of the pretrained model to improve accuracy , Comparing multiple architectures such as ResNet and DenseNet , Incorporating advanced techniques such as attention mechanisms , Using larger and more diverse datasets for improved generalization , Developing a web or mobile application for real-time predictions , Integrating explainable AI techniques such as Grad-CAM for interpretability and Extending classification to multi-stage cancer detection

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