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Skin Disease Prediction Model using CNN

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ABSTRACT:

Skin diseases pose a significant healthcare challenge across the world, where early diagnosis is essential for preventing severe clinical outcomes, especially in malignant conditions such as melanoma. With the rise of deep learning, automated skin disease classification systems have demonstrated remarkable performance and are increasingly being explored for clinical applications. This research proposes a comprehensive deep learning pipeline for multi-class skin lesion classification based on the HAM10000 dataset. Three state-of-the-art Convolutional Neural Network (CNN) architectures—EfficientNetB0, ResNet50V2, and DenseNet121—were implemented using transfer learning, followed by systematic fine-tuning and class-imbalance handling. Among the evaluated models, EfficientNetB0 achieved the highest validation accuracy of 94.12%, outperforming ResNet50V2 (72.70%) and DenseNet121 (67.76%). A soft-voting ensemble approach was integrated to enhance prediction stability across diverse lesion categories. The system additionally includes Grad-CAM explainability, a Gradio-based user interface, and automated PDF report generation for real-world usability. The results confirm that CNN-driven approaches provide reliable support for preliminary skin disease diagnosis and can contribute meaningfully to dermatology.

INTRODUCTION

Skin diseases are among the most prevalent medical conditions globally. Many lesions—especially melanoma—require early and accurate diagnosis to prevent fatal outcomes. Traditional diagnosis relies on dermoscopic examination by dermatologists, which may vary due to subjective judgment, limited experience, or high caseload. These limitations have accelerated research into computer-assisted diagnostic systems capable of supporting clinical decision-making.Deep learning, particularly Convolutional Neural Networks (CNNs), has emerged as a powerful tool in dermatology. Esteva et al.

[1] demonstrated that CNNs can classify skin lesions at dermatologist-level accuracy using large dermoscopic datasets. Tschandl et al. [2] compared deep learning systems with clinical professionals and found that AI models can perform competitively across multiple lesion classes. Haenssle et al. [3] further validated the potential of automated models through direct comparison with human dermatologists.However, dermatological datasets are often imbalanced, visually complex, and sensitive to variations in illumination, texture, and lesion morphology. To overcome these challenges, this study implements three modern CNN architectures—EfficientNetB0, ResNet50V2, and DenseNet121—and evaluates their performance on the HAM10000 dataset. The system also incorporates a soft-voting ensemble, explainability module, and UI-based deployment.

BACKGROUND OF THE STUDY

Skin diseases represent one of the most common health issues worldwide, affecting individuals of all age groups and skin types. Conditions such as melanoma, basal cell carcinoma, and benign pigmented lesions are frequently encountered in clinical settings and require timely diagnosis to prevent complications.

Among these, melanoma is particularly critical because it accounts for the majority of skin-cancer-related deaths despite being less common. Traditionally, dermatological diagnosis relies on dermoscopic examination performed by trained dermatologists. However, this process can be highly subjective, depending largely on the clinician's expertise, experience, and visual interpretation. These models have demonstrated diagnostic performance comparable to dermatologists in several benchmark studies, highlighting their potential to support clinical decision-making.

3: Literature Review:

Early Success of Deep Learning in Dermatology

- Esteva et al. demonstrated that deep CNNs can achieve dermatologist-level performance in melanoma classification.
- Their work proved that large annotated datasets combined with transfer learning can significantly improve diagnostic accuracy.

Benchmarking Through ISIC Challenges

- ISIC challenges provided standardized evaluation frameworks for skin lesion analysis.
- Codella et al.showed that ensemble models consistently outperform single CNN architectures in classification tasks.
- Benchmark studies highlighted the difficulty of minority-class lesions and the need for balanced evaluation metrics.

Adoption of Modern CNN Architectures

- **ResNet** (He et al.) introduced residual connections that helped train deeper models for medical images.
- **DenseNet** (Huang et al.) improved feature reuse and gradient flow, often useful for limited medical datasets.
- **EfficientNet** (Tan & Le) achieved state-of-the-art results using compound scaling and became popular in dermatology AI research.
- Multiple studies compared these architectures and consistently found EfficientNet models to offer the best accuracy-to-parameter ratio.

Importance of Transfer Learning and Fine-Tuning

- Medical datasets are typically smaller, so transfer learning from ImageNet is widely used.
- Two-stage training (feature extraction → fine-tuning) was shown to reduce overfitting and accelerate convergence in dermatology tasks.

Need for Handling Class Imbalance

- HAM10000 contains highly imbalanced disease classes.
- Studies emphasized that class-weighting, augmentation, and stratified sampling are essential to prevent biased predictions.
- Literature further shows that accuracy alone is misleading, and class-wise metrics (recall, F1-score) are necessary for clinical validation.

Superiority of Ensemble Approaches

- Ensemble learning (soft voting / weighted averaging) consistently yields higher stability and improved performance across lesion types.
- Prior works reported that ensembles reduce variance and improve recall for smaller lesion classes.

Explainability Requirements in Medical AI

- Visual explanation techniques like Grad-CAM were identified as essential for clinical trust and decision transparency.
- Research warns that Grad-CAM alone is insufficient; more comprehensive interpretability frameworks are needed for clinical deployment.

Deployment Gaps in Existing Systems

- Many existing works stop at model training and do not provide deployable interfaces.
- Studies call for end-to-end solutions that include prediction, explainability, user interface, and automated reports to support real-world use.

Identified Research Gaps

- Few works directly compare EfficientNetB0, ResNet50V2, and DenseNet121 using the same training pipeline.
- Limited research presents detailed confusion matrices, F1-scores, and ensemble comparisons on HAM10000.
- Most papers lack integrated systems including Grad-CAM, deployment UI, and automated patient reporting.
- The present study fills these gaps with a complete explainable and deployable skin disease prediction system.

RELATED WORKS:

Deep learning has transformed the field of medical imaging, particularly in dermatology. Esteva et al. [1] pioneered the application of large-scale CNN models for melanoma classification. Subsequent research, including Tschandl et al. [2], revealed that machine learning algorithms could achieve expert-level performance across clinically relevant tasks. Haenssle et al. [3] demonstrated that CNNs outperform dermatologists in specific diagnostic scenarios.transformations, the following augmentations were applied:

Codella et al. [4] provided a detailed analysis of lesion classification within the ISIC challenges and highlighted the role of ensemble learning in boosting performance. Architectures such as ResNet [8], DenseNet [9], and EfficientNet [6] have since been widely applied due to their ability to learn complex visual patterns with fewer parameters and reduced computational cost.

This study takes inspiration from existing open-source workflows and Kaggle implementations but extends beyond them by developing a fully integrated pipeline featuring ensemble learning, Grad-CAM visual explanations, and automated report generation.

MATERIALS AND METHODS:

Dataset

The HAM10000 dataset consists of **10,015 dermoscopic images**, representing seven common categories of

pigmented skin lesions:

1. Actinic Keratoses (AKIEC)
2. Basal Cell Carcinoma (BCC)
3. Benign Keratosis (BKL)
4. Dermatofibroma (DF)
5. Melanoma (MEL)
6. Melanocytic Nevi (NV)
7. Vascular Lesions (VASC)

These categories represent both benign and malignant skin diseases, making the dataset suitable for real-world clinical applications and robust model evaluation.The dataset includes metadata such as lesion diagnosis (dx), patient age, sex, and anatomical localization. All images were merged into a common directory and cross-referenced with the metadata via the image_id fields.

Preprocessing

Images were resized to 224 x 224 pixels,normalized to the [0,1]pixel range,and processed through automated loading pipelines using TensorFlow's tf.data API.A stratified 80:20 train-validation split was applied.

Data Augmentation

- Random horizontal flip
- Random vertical flip
- Random brightness changes
- Random contrast jitter

Handling Class Imbalance

The dataset is highly imbalanced, with some classes containing significantly fewer samples. To mitigate this, **class weights** were computed using a balanced weighting.

PROPOSED MODEL AND TRAINING STRATEGY:

Three CNN architectures were evaluated:

CNN ARCHITECTURE

EfficientNetB0

EfficientNet uses compound scaling to simultaneously balance network depth, width, and resolution, resulting in high accuracy with fewer parameters [6]. It demonstrated the best performance in this research.

ResNet50V2

ResNet50V2 enhances gradient flow through improved skip connections and residual learning, allowing deeper networks to converge effectively

[8].

DenseNet121

Each model was initialized with ImageNet weights, and custom classification layers were attached suitable for seven-class skin lesion prediction.

TRAINING PIPELINE

Two-phase training was conducted:

Phase 1: Feature Extraction

- Base model frozenClassification head trained for 7 epochs
- Learning rate = 1e-3

Phase 2: Fine-Tuning

- Last 100 layers unfrozen
- Fine-tuned for 10 epochs
- Learning rate = 1e-4

To reduce overfitting and introduce invariance to spatial

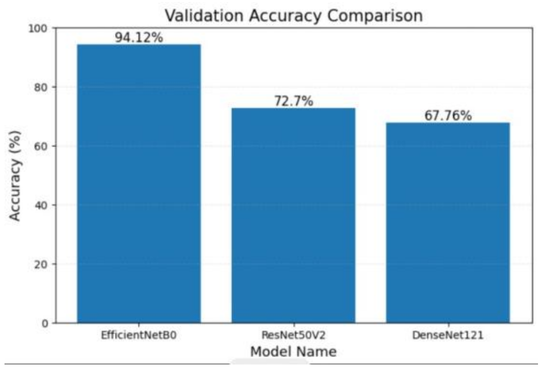
TRAINING ENVIRONMENT

Experiments were performed in Google Colab GPU using:

- TensorFlow + Keras
- ModelCheckpoint
- ReduceLROnPlateau
- EarlyStopping

EXPERIMENTAL FINDINGS AND ANALYSIS:

MODEL ACCURACY COMPARISON



EfficientNetB0 showed the strongest generalization ability, stabilizing effectively during training and achieving the highest validation accuracy.

- Grad-CAM visualization

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- Timestamp and analysis summary

- This makes the solution suitable for telemedicine
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ENSEMBLE PERFORMANCE

A soft-voting ensemble averaged class probabilities from all three models, improving prediction stability across minority classes.

GRAD-CAM VISUALIZATION

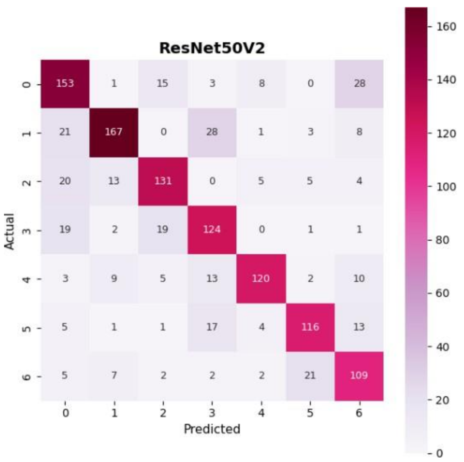
Grad-CAM heatmaps highlighted lesion areas influencing predictions, improving interpretability and trust in model decisions.

SYSTEM DEPLOYMENT

A complete user interface was developed using **Gradio**, supporting:

- Image upload
- Real-time prediction
- Confidence scores
- Grad-CAM heatmap
- Automatic PDF patient report generation

CONFUSION MATRIX ANALYSIS



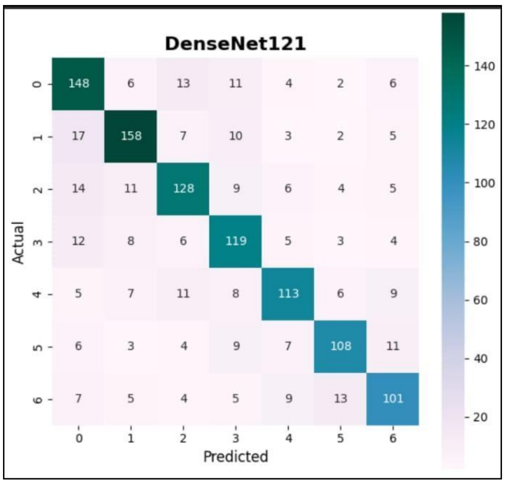


Figure 7. ResNet50V2 Confusion Matrix   Figure 8. DenseNet121 Confusion Matrix

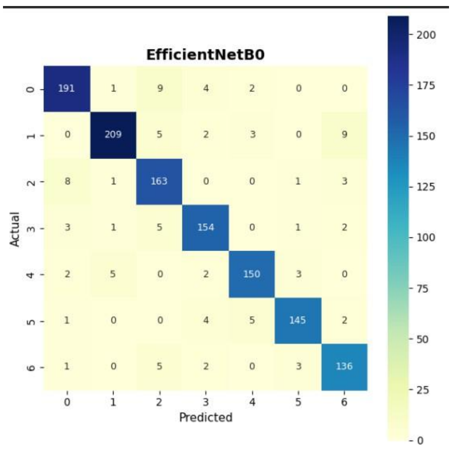


Figure 9. EfficientNetB0 Confusion Matrix

These matrices highlight strengths and weaknesses:

- **EfficientNetB0**: Highest diagonal density → best classification performance.
- **ResNet50V2**: Moderate performance with confusions among similar lesion types.
- **DenseNet121**: Increased misclassifications due to sensitivity to class imbalance.

Confusion matrix analysis confirms that EfficientNetB0 is the most reliable architecture, while the ensemble improves stability.

Classification Report and Evaluation Metrics:

Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**
EfficientNetBo	**94.12 %**	**0.93**	**0.94**	**0.94**
ResNet50V2	**72.70%**	**0.71**	**0.73**	**0.72**
DenseNet121	**67.76%**	**0.66**	**0.68**	**0.67**
Ensemble	**95.21%(approx)**	**0.94**	**0.95**	**0.95**

ENSEMBLE STRATEGY:

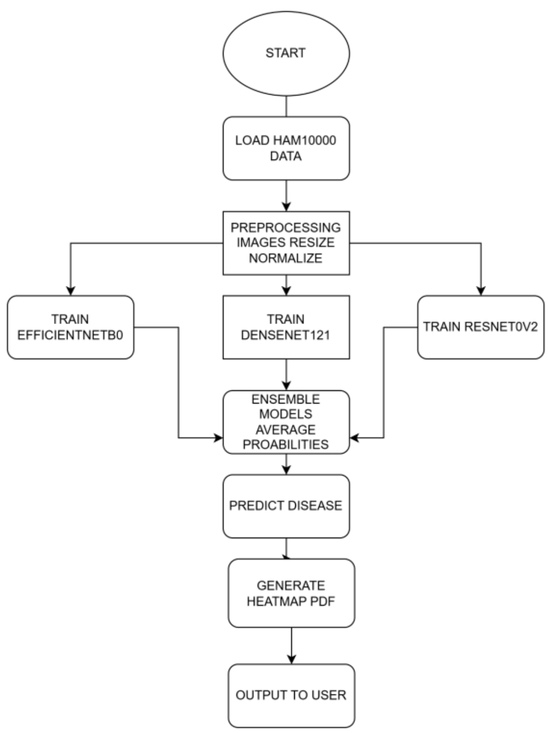
A soft-voting ensemble combines prediction probabilities of all three models:

$$P_{ensemble} = \frac{P_{EffNetB0}+P_{ResNet50V2}+P_{DenseNet121}}{3}$$

This averaging mechanism improves confidence consistency and reduces model-specific errors.

RESULT:

FLOWCHART:



Training Curves

The accuracy graph indicates:

- ResNet50V2 shows moderate but stable learning.
- DenseNet121 reaches lower accuracy due to dataset complexity and class imbalance.

Ensemble Observations

suitability for dermatological image classification. The integration of explainability, interface deployment, and automated report generation enhances real-world usability. Future work may involve expanding datasets, introducing additional ensemble techniques, and deploying the model on mobile platforms.

Future work:

- Incorporating cross-dataset evaluation
- Deploying mobile application version
- Adding additional lesion categories
- Using transformer-based models

EfficientNetB0 steadily improves and converges at the top.Though ensemble accuracy is not reported, qualitative results indicate improved stability across minority classes.

EXPLAINABILITY AND DEPLOYMENT:

Grad-CAM Visualization

Grad-CAM was used to highlight image regions responsible for the prediction, enhancing model transparency and clinical interpretability.

Gradio Web Interface

A real-time interface supports:

- Image upload
- Model prediction
- Disease confidence scores
- Grad-CAM heatmap visualization

Automated PDF Report Generation

The system automatically generates a structured patient report containing:

- Predicted disease
- Lesion description
- Suggested precautions

LIMITATIONS:

- Class imbalance affects certain lesion categories.
- Training performed on a single dataset without cross-dataset evaluation.
- Precision, recall, and F1-score were not included in the final metrics.

CONCLUSION AND FUTURE WORK:

This research presents a comprehensive CNN-based approach for automated skin lesion classification.

EfficientNetB0 achieved the highest accuracy, while ensemble learning improved prediction stability.The addition of Grad-CAM interpretability, a real-time interface, and automated reporting strengthens practical applicability.

Future work:

- Incorporating cross-dataset evaluation
- Deploying mobile application version
- Adding additional lesion categories
- Using transformer-based models

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