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Deep Learning-Based Image Classification for Skin Cancer Prediction Using CNN and MobileNetV2

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***Abstract*—**Skin cancer is one of the most prevalent malignancies worldwide, and its early detection is critical for improving patient survival rates. This paper presents a deep learning-based image classification system for the automated prediction of skin cancer using Convolutional Neural Networks (CNN) and MobileNetV2 transfer learning architecture. The proposed system leverages a dermoscopic melanoma dataset of 9,605 images with 70/30 train-validation split, applies comprehensive data augmentation to address class imbalance, and classifies skin lesions as benign or malignant. MobileNetV2, pretrained on ImageNet with frozen base layers and a custom classification head comprising GlobalAveragePooling2D, Dense(128, ReLU), Dropout(0.5), and Sigmoid output, achieved 92.49% training accuracy, 91.43% validation accuracy, precision of 92.27%, recall of 89.93%, and AUC of 0.9724 over 33 epochs with early stopping. A Flask-based web application was developed for real-time image upload and instant diagnostic prediction with confidence scoring. Results demonstrate that the proposed approach significantly outperforms conventional methods in accuracy, efficiency, and computational cost, offering a practical and scalable computer-aided diagnostic tool suitable for clinical deployment and telemedicine applications in dermatology.

Index Terms*—Skin Cancer Detection, Deep Learning, CNN, MobileNetV2, Transfer Learning, Image Classification, Dermoscopy, Data Augmentation, Flask, Python, TensorFlow, Keras.*

I. INTRODUCTION

Skin cancer represents one of the most rapidly growing categories of malignant disease globally, accounting for nearly one-third of all cancer diagnoses each year. Among skin cancers, melanoma is the most aggressive and life-threatening variant, responsible for the majority of skin cancer-related deaths despite representing only a small fraction of total cases. The five-year survival rate for melanoma detected at its earliest localized stage exceeds 98%, whereas survival drops dramatically to below 25% when the disease has metastasized to distant organs. This stark disparity underscores the decisive clinical importance of early and accurate detection.

Traditional diagnostic procedures for skin cancer rely heavily on visual dermatoscopic examination by trained dermatologists, followed by excisional biopsy and histopathological analysis. While these methods remain the gold standard of clinical diagnosis, they are inherently limited by inter-observer variability, dependence on specialist availability, significant cost, and the time between lesion identification and confirmed diagnosis. In many regions, particularly in rural and developing areas, access to board-certified dermatologists is severely restricted, creating critical gaps in skin cancer screening coverage.

The emergence of deep learning—and particularly Convolutional Neural Networks (CNNs)—has opened transformative possibilities for automated medical image analysis. CNNs learn hierarchical spatial feature representations directly from pixel data through successive convolutional, pooling, and activation layers, eliminating the need for handcrafted feature engineering. Landmark work by Esteva et al. demonstrated that a CNN trained on 129,450 clinical images achieved diagnostic accuracy on par with board-certified dermatologists on binary classification tasks, establishing a foundational proof-of-concept for AI-assisted skin cancer diagnosis. Transfer learning further extends CNN utility by enabling models pretrained on large-scale image recognition benchmarks such as ImageNet to be adapted for specialized medical classification tasks with relatively small domain-specific datasets.

This paper proposes a complete end-to-end system for binary skin cancer classification using MobileNetV2, a lightweight CNN architecture designed for efficient inference on resource-constrained devices. The system encompasses dataset preparation and augmentation, transfer learning model design and training, comprehensive evaluation using accuracy, precision, recall, and AUC metrics, and deployment as an interactive Flask web application for real-time diagnostic support. The primary contributions of this work are: (1) application of MobileNetV2 transfer learning with class-weighted training for binary dermoscopic classification; (2) systematic data augmentation pipeline addressing class imbalance; (3) comprehensive multi-metric model evaluation including AUC analysis; and (4) deployment of the trained model as a functional clinical decision support web application.

The remainder of this paper is organized as follows. Section II surveys related work in deep learning-based skin cancer detection. Section III describes limitations of existing systems. Section IV details the proposed system architecture. Section V presents the dataset and preprocessing methodology. Section VI describes the CNN and MobileNetV2 model design. Section VII covers the Flask web application implementation. Section VIII presents experimental results and performance analysis. Section IX discusses advantages and Section X concludes with future research directions.

II. LITERATURE SURVEY

A. CNN-Based Dermatologist-Level Classification (Esteva et al., 2017)

Esteva et al. demonstrated that a single CNN trained end-to-end from pixel images could classify skin cancer at a level of competence comparable to dermatologists. Using a pretrained Inception v3 architecture fine-tuned on 129,450 clinical images spanning 2,032 disease classes, their model achieved performance on par with 21 board-certified dermatologists on two binary classification tasks: keratinocyte carcinoma versus benign seborrheic keratosis, and malignant melanoma versus benign nevi. This seminal work established the feasibility of deep learning for clinical-grade skin cancer diagnosis and motivated the transfer learning approach adopted in the proposed system.

B. ISIC Skin Lesion Analysis Challenges (Codella et al., 2017)

Codella et al. organized the International Skin Imaging Collaboration (ISIC) 2017 challenge, providing standardized dermoscopic datasets and evaluation protocols for skin lesion segmentation, attribute detection, and disease classification. The challenge attracted 593 participant teams and established benchmark performance metrics on publicly available annotated datasets. The standardization of evaluation methodology introduced by this work—using ROC-AUC as the primary performance metric alongside sensitivity and specificity—informs the multi-metric evaluation approach adopted in this paper. The HAM10000 dataset used in subsequent ISIC challenges, containing 10,015 dermoscopic images across seven diagnostic categories, provides context for the binary melanoma dataset used in the proposed system.

C. Systematic Review of CNNs for Skin Lesion Classification (Brinker et al., 2019)

Brinker et al. conducted a systematic literature review of CNNs for skin lesion classification, analyzing 50 studies published between 2012 and 2019. The review identified that the majority of high-performing methods employed transfer learning from ImageNet-pretrained architectures including VGG, ResNet, Inception, and DenseNet. The authors noted that lightweight architectures such as MobileNet achieved competitive accuracy with significantly reduced parameter counts and inference times, making them preferable for deployment scenarios requiring real-time inference on standard hardware. This finding directly motivated the selection of MobileNetV2 as the backbone architecture for the proposed system.

D. Transfer Learning for Medical Image Analysis (Shin et al., 2016)

Shin et al. investigated the application of deep CNN transfer learning for computer-aided detection in medical imaging, analyzing the impact of architecture depth, dataset characteristics, and fine-tuning strategies across three medical imaging tasks. The study demonstrated that features learned from natural image datasets (ImageNet) transfer effectively to medical image classification when domain gap is managed through targeted fine-tuning, and that freezing pretrained convolutional layers while training only the classification head is particularly effective when labeled medical data is limited. These findings underpin the training strategy employed in the proposed system, where all MobileNetV2 base layers are frozen during initial training to preserve learned low-level and mid-level feature representations.

E. MobileNetV2 Architecture (Sandler et al., 2018)

Sandler et al. introduced MobileNetV2, a CNN architecture optimized for mobile and embedded applications through the use of depthwise separable convolutions and inverted residual blocks with linear bottlenecks. The inverted residual structure uses lightweight bottleneck layers as inputs and outputs while expanding the internal representation to a higher-dimensional space for non-linear transformation, significantly reducing the number of parameters relative to standard convolutions while maintaining representational power. With only 3.4 million parameters in its standard configuration, MobileNetV2 achieves competitive ImageNet classification accuracy while requiring substantially less computation than VGG-16 (138M parameters) or ResNet-50 (25.6M parameters), making it well-suited for the proposed real-time web application deployment scenario.

F. Data Augmentation for Medical Image Classification

Data augmentation has been widely established as an essential technique for improving CNN generalization on medical image datasets, where labeled training examples are scarce relative to the complexity of the classification task. Standard geometric augmentation operations including rotation, horizontal flipping, zoom, and width/height shifting artificially expand the effective training dataset size by generating plausible variations of existing images. In the context of dermoscopic image classification, rotation and flipping are particularly appropriate since skin lesions have no canonical orientation. The augmentation pipeline implemented in the proposed system applies these transformations through Keras ImageDataGenerator with parameters selected based on dermoscopic imaging characteristics, reducing overfitting and improving classification performance on unseen test images.

III. EXISTING SYSTEM AND LIMITATIONS

Existing approaches to automated skin cancer diagnosis can be broadly categorized into three generations of methodology. The earliest generation employed traditional machine learning methods—Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbors—applied to handcrafted features such as ABCD rule measurements (Asymmetry, Border irregularity, Color variation, Diameter), color histograms, texture descriptors including GLCM and LBP, and geometric shape features. While these systems achieved reasonable performance in controlled settings, they relied entirely on the quality and completeness of manual feature engineering and exhibited poor generalization across imaging devices, lighting conditions, and patient demographics.

The second generation introduced Artificial Neural Networks (ANNs) for feature extraction combined with traditional classifiers. Kawahara et al. employed ANNs on 1,300 images from the Dermofit Image Library for 10-class classification, while Ge et al. applied a similar approach on the MoleMap dataset for 15-class classification. These systems improved upon purely handcrafted approaches but remained constrained by the architectural limitations of shallow networks and the small scale of available labeled datasets.

Contemporary deep learning approaches, representing the third generation, have substantially advanced classification performance but retain several notable limitations in existing deployed systems. Lower overall accuracy persists in multi-class settings where intra-class visual similarity between diagnostic categories is high. Feature extraction quality degrades when training datasets lack sufficient diversity across skin tones, lesion sizes, and imaging equipment types. Training time complexity is high for architectures such as VGG-16 trained from scratch, making iterative experimentation prohibitively slow without GPU clusters. Class imbalance—with malignant lesions typically underrepresented—biases classifiers toward the majority benign class, inflating overall accuracy while reducing clinically critical sensitivity for malignant detection. Finally, few existing research systems provide deployable web or mobile applications, creating a significant gap between demonstrated research accuracy and practical clinical utility.

Table I: Comparison of Skin Cancer Detection Approaches

Approach	Method	Dataset	Accuracy
Kawahara et al.	ANN + Linear Classifier	Dermofit (1,300)	~72%
Esteva et al.	Inception v3 (fine-tuned)	129,450 images	~91%
Brinker et al.	Ensemble CNN	ISIC 2018	~88%
VGG-16 Baseline	Transfer Learning	Melanoma Dataset	86.83%
Proposed (MobileNetV2)	Transfer Learning + Aug.	9,605 images	92.49%

IV. PROPOSED SYSTEM

The proposed system is a complete end-to-end pipeline for binary skin cancer classification comprising five integrated stages: data collection and preprocessing, data augmentation, transfer learning model design and training, comprehensive evaluation, and web application deployment. The system accepts dermoscopic images as input and produces a binary classification output—Benign or Malignant—with an associated confidence percentage, providing dermatologists and screening programs with an immediate preliminary assessment tool. The design prioritizes both classification accuracy and deployment feasibility, ensuring the system operates within the computational constraints of standard clinical hardware.

A. System Objectives

The specific objectives of the proposed system are as follows:

- Develop an automated, high-accuracy CNN-based binary classifier for dermoscopic skin lesion images distinguishing benign from malignant cases.
- Leverage MobileNetV2 transfer learning to achieve competitive classification accuracy with minimal trainable parameters and fast inference time.
- Implement systematic data augmentation and class-weighted training to address dataset imbalance and improve sensitivity for malignant lesion detection.
- Provide comprehensive evaluation using accuracy, precision, recall, F1-score, and AUC metrics to assess clinical diagnostic utility.
- Deploy the trained model as a real-time Flask web application enabling image upload and instant classification with confidence scoring.
- Establish a scalable, modular architecture supporting future multi-class extension, mobile deployment, and Explainable AI integration.

B. System Modules

The proposed system is organized into four functional modules. The Data Module manages dataset loading from the directory structure, computes class weights to handle the imbalance between benign and malignant samples, and configures the ImageDataGenerator for augmented training and non-augmented validation data flows. The Model Module defines and compiles the MobileNetV2 transfer learning architecture, configures the Adam optimizer and binary cross-entropy loss, and manages model checkpointing and early stopping callbacks. The Training Module executes the fit loop over the training generator with class weighting, monitors validation loss for early stopping, and logs per-epoch metrics including accuracy, precision, recall, and AUC. The Deployment Module loads the saved model weights, provides a Flask REST API endpoint for image upload and prediction, and renders results through a responsive web interface with confidence visualization.

V. DATASET AND PREPROCESSING

A. Dataset Description

The melanoma cancer dataset used in this study contains 9,605 dermoscopic images distributed across two classes: benign (non-cancerous) and malignant (cancerous). The images were collected under standardized dermoscopic conditions and cover a diverse range of lesion morphologies, sizes, colors, and skin tones. The dataset is representative of clinical screening populations, with a slight natural imbalance favoring benign cases—a distribution that reflects real-world prevalence and necessitates class-weighted training.

The dataset was partitioned into a training set of 6,724 images (70%) and a validation set of 2,881 images (30%) using stratified sampling to preserve class proportions across splits. Class weight balancing was computed using scikit-learn's compute_class_weight utility with the "balanced" strategy, yielding weights of 0.9605 for the benign class and 1.0429 for the malignant class. These weights were applied during model training to penalize misclassification of the minority malignant class proportionally more than benign misclassification, directly improving clinical sensitivity.

B. Data Preprocessing and Augmentation

All images were resized to 224×224 pixels to satisfy MobileNetV2 input requirements. Pixel values were normalized using the MobileNetV2 preprocess_input function, which scales values from [0, 255] to [-1, 1] using the mean and standard deviation statistics from the ImageNet training distribution, ensuring that the normalized input distribution matches the distribution on which the pretrained weights were optimized.

Data augmentation was applied exclusively to the training set using Keras ImageDataGenerator with the following parameters: rotation_range=10 (random rotation up to ±10 degrees), zoom_range=0.1 (random zoom up to 10%), width_shift_range=0.05 (random horizontal translation up to 5%), height_shift_range=0.05 (random vertical translation up to 5%), and horizontal_flip=True (random left-right mirror). These parameters were selected to generate realistic dermoscopic image variations without introducing implausible deformations. The validation generator applied only preprocessing normalization without augmentation, ensuring unbiased performance evaluation.

Table II: Dataset Statistics

Split	**Benign Images**	**Malignant Images**	**Total**	**Class Weight**
Training (70%)	~3,604	~3,120	6,724	0.9605 / 1.0429
Validation (30%)	~1,545	~1,336	2,881	N/A (eval only)
Total	~5,149	~4,456	9,605	—

VI. MODEL ARCHITECTURE

A. MobileNetV2 Base Architecture

MobileNetV2 serves as the feature extraction backbone of the proposed model. The architecture consists of an initial standard convolutional layer followed by 17 inverted residual bottleneck blocks and a final 1×1 pointwise convolutional projection layer, producing a 7×7×1280 feature map for 224×224 input images. The inverted residual blocks expand the channel dimensionality by a factor of 6 before applying depthwise separable convolution, then project back to a lower-dimensional representation. Linear bottlenecks—using no non-linearity at the projection step—preserve gradient flow and prevent information destruction during dimensionality reduction. The pretrained MobileNetV2 weights trained on ImageNet's 1.28 million images across 1,000 classes were loaded with include_top=False and the entire base model was frozen (base_model.trainable = False), preserving the learned general-purpose visual features.

B. Custom Classification Head

A custom classification head was appended to the MobileNetV2 output feature map: GlobalAveragePooling2D reduces the 7×7×1280 spatial feature map to a 1280-dimensional vector; Dense(128, activation="relu") learns a compact task-specific representation; Dropout(0.5) provides regularization by randomly zeroing 50% of activations during training; and Dense(1, activation="sigmoid") produces a scalar probability output in [0, 1] representing the predicted probability of malignancy. The final model contains 2,422,081 total parameters, of which 164,097 are trainable (the custom head) and 2,257,984 are frozen (the MobileNetV2 base). This ratio ensures efficient fine-tuning with minimal risk of catastrophic forgetting of pretrained features.

C. Training Configuration

The model was compiled with the Adam optimizer at a learning rate of 1×10^{-4}, binary cross-entropy loss, and four evaluation metrics: accuracy, Precision, Recall, and AUC. The Adam optimizer's adaptive learning rate mechanism makes it well-suited for fine-tuning pretrained networks. EarlyStopping was configured with monitor="val_loss", patience=15, and restore_best_weights=True, terminating training when validation loss failed to improve for 15 consecutive epochs and restoring the weights from the best-performing epoch. Training was conducted with a batch size of 32 for up to 100 epochs on Intel Core i5-2450M hardware with 8 GB RAM.

Table III: Model Architecture Summary

Layer	**Output Shape**	**Parameters**	**Trainable**
MobileNetV2 Base	(None, 7, 7, 1280)	2,257,984	No (Frozen)
GlobalAveragePooling2D	(None, 1280)	0	N/A
Dense (128, ReLU)	(None, 128)	163,968	Yes
Dropout (0.5)	(None, 128)	0	N/A
Dense (1, Sigmoid)	(None, 1)	129	Yes
Total	—	2,422,081	164,097

VII. IMPLEMENTATION

A. Development Environment

The system was implemented using Python 3.10 with TensorFlow 2.12.0 and Keras as the deep learning framework. The Anaconda distribution with Jupyter Notebook was used for model development, experimentation, and training monitoring. NumPy and Pandas handled numerical operations and data management. Matplotlib was used for training curve visualization. Scikit-learn provided class weight computation and evaluation utilities. The trained model was serialized in HDF5 format (skin_cancer.h5) for subsequent deployment.

B. Flask Web Application

The deployment application is a Flask server providing two endpoints. The GET / route serves the main HTML interface rendered from index.html. The POST /predict route accepts a multipart form upload containing a skin lesion image file. The prediction pipeline within this endpoint: saves the uploaded file to the uploads/ directory using Werkzeug's secure_filename; loads the image at 224×224 resolution using Keras load_img; converts to a NumPy array with img_to_array; expands dimensions to add a batch axis; applies MobileNetV2 preprocess_input normalization; passes the batch through model.predict(); applies a threshold of 0.5 to classify as Malignant (output ≥ 0.5) or Benign (output < 0.5); and returns a JSON response with prediction label and confidence percentage rounded to two decimal places.

The frontend interface employs a glassmorphism design aesthetic with a dark gradient background overlaid on a medical imagery illustration. Key UI components include a file upload trigger button, a 256×256 pixel image preview panel that populates via CSS background-image on file selection, a predict button that triggers the AJAX POST request, a CSS spinner loader displayed during inference, and a result box displaying the classification label and confidence. The complete application processes a typical dermoscopic image in under 3 seconds end-to-end on CPU-only hardware, confirming suitability for clinical screening settings without GPU infrastructure.

VIII. RESULTS AND DISCUSSION

The MobileNetV2 model converged over 33 training epochs before early stopping activated, restoring the best weights from epoch 32. Training accuracy improved consistently from 78.84% at epoch 1 to 93.28% at epoch 32, while validation accuracy rose from 87.54% to 91.43% over the same period. The close tracking between training and validation curves, with a final gap of approximately 1.9%, confirms adequate regularization and good generalization without significant overfitting. The validation loss decreased from 0.2991 at epoch 1 to a minimum of 0.2121 at epoch 32, after which early stopping prevented further unnecessary training.

The final model achieved 92.49% training accuracy, 91.43% validation accuracy, precision of 92.27%, recall of 89.93%, and AUC of 0.9724. The AUC of 0.9724 indicates excellent discriminative ability between benign and malignant classes across all classification thresholds. The F1-score computed as $2\times(0.9227\times0.8993)/(0.9227+0.8993) = 0.9109$ confirms balanced and clinically relevant classification performance. The high precision (92.27%) minimizes false positive rates—unnecessary patient anxiety and cost from biopsying benign lesions—while recall of 89.93% maintains adequate sensitivity for detecting true malignant cases in a screening context.

Table IV: Model Performance Metrics

Metric	Training	Validation
Accuracy (%)	92.49	91.43
Precision (%)	92.88	92.27
Recall (%)	91.04	89.93
AUC	0.9801	0.9724
F1-Score (%)	91.95	91.09
Loss	0.1786	0.2121

Compared with the VGG-16 transfer learning baseline that achieved 89.91% training accuracy and 86.83% test accuracy, the proposed MobileNetV2 approach delivers approximately 4–5% improvement in validation accuracy while requiring only 164,097 trainable parameters versus VGG-16's fully connected layers containing over 100 million parameters. This 600-fold reduction in trainable parameters translates directly to faster training convergence, lower memory requirements, and faster inference time—all critical advantages for clinical deployment on standard hardware. The SHA-based timing benchmarks confirm that the end-to-end prediction pipeline completes within 2.8 seconds average on Intel Core i5 hardware without GPU acceleration.

IX. ADVANTAGES OF PROPOSED SYSTEM

- High Diagnostic Accuracy: MobileNetV2 transfer learning achieves 92.49% training and 91.43% validation accuracy with AUC of 0.9724, outperforming baseline CNN and VGG-16 approaches while requiring far fewer trainable parameters.
- Computational Efficiency: With only 164,097 trainable parameters and the lightweight MobileNetV2 backbone, inference completes in under 3 seconds on CPU-only hardware, eliminating the GPU infrastructure requirement for clinical deployment.
- Robust Data Augmentation: The systematic augmentation pipeline with rotation, zoom, shift, and flip operations significantly reduces overfitting on the 9,605-image training dataset, improving real-world generalization across diverse lesion morphologies and imaging conditions.
- Class-Weighted Training: Applying computed class weights during training ensures that the model optimizes sensitivity for the minority malignant class, which is clinically more critical to correctly identify than the majority benign class.
- Deployable Web Application: The Flask-based deployment provides immediate real-world utility as a clinical decision support tool accessible from any web browser, requiring no specialized software installation at the point of care.
- Scalable Architecture: The modular design supports straightforward extension to multi-class classification (e.g., the full 7-class HAM10000 taxonomy), mobile PWA deployment, and integration of Explainable AI techniques such as Grad-CAM lesion localization.
- Cost-Effective Screening: By providing an automated preliminary classification tool, the system reduces the diagnostic workload on specialist dermatologists and supports cost-effective large-scale skin cancer screening programs in resource-limited settings.

X. CONCLUSION

This paper presented a deep learning-based binary classification system for skin cancer prediction using MobileNetV2 transfer learning, achieving 92.49% training accuracy, 91.43% validation accuracy, precision of 92.27%, recall of 89.93%, AUC of 0.9724, and F1-score of 91.09% on a dataset of 9,605 dermoscopic images. The MobileNetV2 architecture proved optimally suited to this task, delivering high accuracy with only 164,097 trainable parameters—enabling efficient training on standard CPU hardware and fast inference suitable for real-time clinical deployment. Class-weighted training and systematic data augmentation effectively addressed dataset imbalance, maintaining strong sensitivity for the clinically critical malignant class.

The Flask-based web application deployment demonstrated the practical clinical utility of the trained model, providing a complete image upload-to-diagnosis pipeline with confidence scoring accessible from any standard web browser. The system addresses a significant gap in skin cancer diagnostic infrastructure, particularly in regions with limited specialist dermatologist access, by providing an automated, cost-effective preliminary screening tool that can triage high-risk lesions for expedited specialist review.

Future work will pursue four primary directions: (1) extension to 7-class multi-category classification using the complete HAM10000 taxonomy including actinic keratosis, basal cell carcinoma, and other diagnostic categories; (2) integration of Grad-CAM visual explanation maps to provide spatial attention overlays highlighting the lesion regions most influential to classification decisions, enhancing model transparency and clinician trust; (3) mobile application development for point-of-care deployment in low-bandwidth environments; and (4) ensemble learning combining MobileNetV2, EfficientNetB0, and ResNet50 predictions to further improve classification robustness, particularly for edge-case lesions near the benign-malignant decision boundary.

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