Skin Cancer Detection Using Deep Learning

Dr. Arvind Jagtap[1]; Nisarg M. Jogdande[2]; Tejasvini V. Shelar[3]; Sahil S. Jadhav[4]; Divya R. Lokhande[5]

[1,2,3,4,5]Computer Engineering Department VPKBIET Baramati, SPPU Pune, Maharashtra, India

Publication Date: 2026/04/28

Abstract: Cutaneous malignancies pose a major worldwide health concern, requiring rapid and accurate detection. Traditional diagnostic approaches, including clinical inspection and biopsy procedures, are time-intensive and necessitate advanced dermatological proficiency. Advancements in artificial intelligence, particularly convolutional neural network models, have demonstrated superior efficacy in classifying dermatological imagery.

The research proposes a diagnostic system for skin cancer detection based on MobileNetV2 via transfer learning. It employs the HAM10000 dataset, encompassing 10,015 dermoscopic images across seven lesion types. The pipeline integrates image preparation, model training, multiclass classification in Python, and web deployment through Flask. Evaluation on the test set yielded 71.38% accuracy, with mean precision of 85.77% and recall of 60.42%. Such a system equips medical professionals with an automated aid for prognostic assessments in clinical practice. Prospective improvements could include dataset augmentation and advanced network designs.

Keywords: *Skin Lesion Identification; Deep Neural Networks; CNN Models; Transfer Learning Techniques; MobileNetV2 Framework; Medical Image Evaluation; Dermoscopy Datasets (HAM10000); Image Preparation Methods; Image Categorization Tasks; CAD Tools; AI-Driven Healthcare Solutions; Automated Screening Systems; Clinical Image Processing.*

How to Cite: Dr. Arvind Jagtap; Nisarg M. Jogdande; Tejasvini V. Shelar; Sahil S. Jadhav; Divya R. Lokhande (2026) Skin Cancer Detection Using Deep Learning. *International Journal of Innovative Science and Research Technology*, 11(4), 2147-2154. https://doi.org/10.38124/ijisrt/26apr1616

I. INTRODUCTION

Skin cancer ranks among the most common cancers globally, mainly arising from extended ultraviolet radiation exposure from the sun, which induces uncontrolled growth in skin cells. It appears in multiple types, such as melanoma, basal cell carcinoma, and squamous cell carcinoma. Among them, melanoma presents the highest risk owing to its tendency for swift spread to remote organs. Early detection thus significantly improves treatment success and survival prospects.

Clinicians conventionally diagnose skin cancer via direct visual examination of the skin, dermoscopy, and biopsy when indicated. Although effective, these methods demand considerable time and depend substantially on dermatologists' expertise. In remote or resource-limited areas, limited access to trained specialists frequently delays detection and treatment.

Over the past decade, artificial intelligence (AI) has emerged as a key advancement in medical image processing. Within deep learning methodologies, Convolutional Neural Networks (CNNs) stand out for their capacity to discern critical structures in clinical imagery via self-supervised feature extraction. Unlike conventional machine learning methods dependent on manually engineered attributes, CNNs operate directly on unprocessed pixel inputs, thereby improving diagnostic reliability and consistency.

The present study proposes a computational system for skin lesion analysis, leveraging deep learning with transfer learning via the MobileNetV2 model to classify dermoscopic images. Its central aim is to create a precise, streamlined tool that assists dermatologists in promptly detecting skin cancer.

➢ *Objectives*

Key aims include developing an artificial intelligence system for detecting skin cancer through deep neural architectures, classifying dermoscopic images into various lesion categories, decreasing dependence on specialist assessments, enabling swift initial screenings, and deploying the optimized model in an accessible web interface.

II. RELATED WORK

Traditional approaches to skin cancer identification utilized standard machine learning algorithms reliant on handcrafted descriptors like pigmentation and surface patterns. Classification models included Support Vector Machines (SVM) alongside k-Nearest Neighbor techniques.

K-nearest neighbors (KNN) algorithms have traditionally supported classification in this field. Recent

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/26apr1616

studies demonstrate that convolutional neural networks (CNNs) achieve notably higher precision. Transfer learning using models like VGGNet, ResNet, and MobileNet reduces training time while enhancing performance. Challenges remain, however, including substantial computational requirements and adaptation for real-time applications.

III. PROPOSED METHODOLOGY

➢ *The Proposed Framework Operates Through the Following Sequential Stages:*

- Submission of a dermoscopic image by the user via the online portal.
- Application of preprocessing operations to optimize image quality.
- Extraction of deep feature embeddings employing the MobileNetV2 architecture.
- Classification executed via fully connected neural layers.
- Computation of class probability distributions using softmax activation.
- Presentation of the classification outcome alongside its confidence value.

The trained model is saved and integrated into a Flask-based web application, enabling real-time skin lesion analysis.

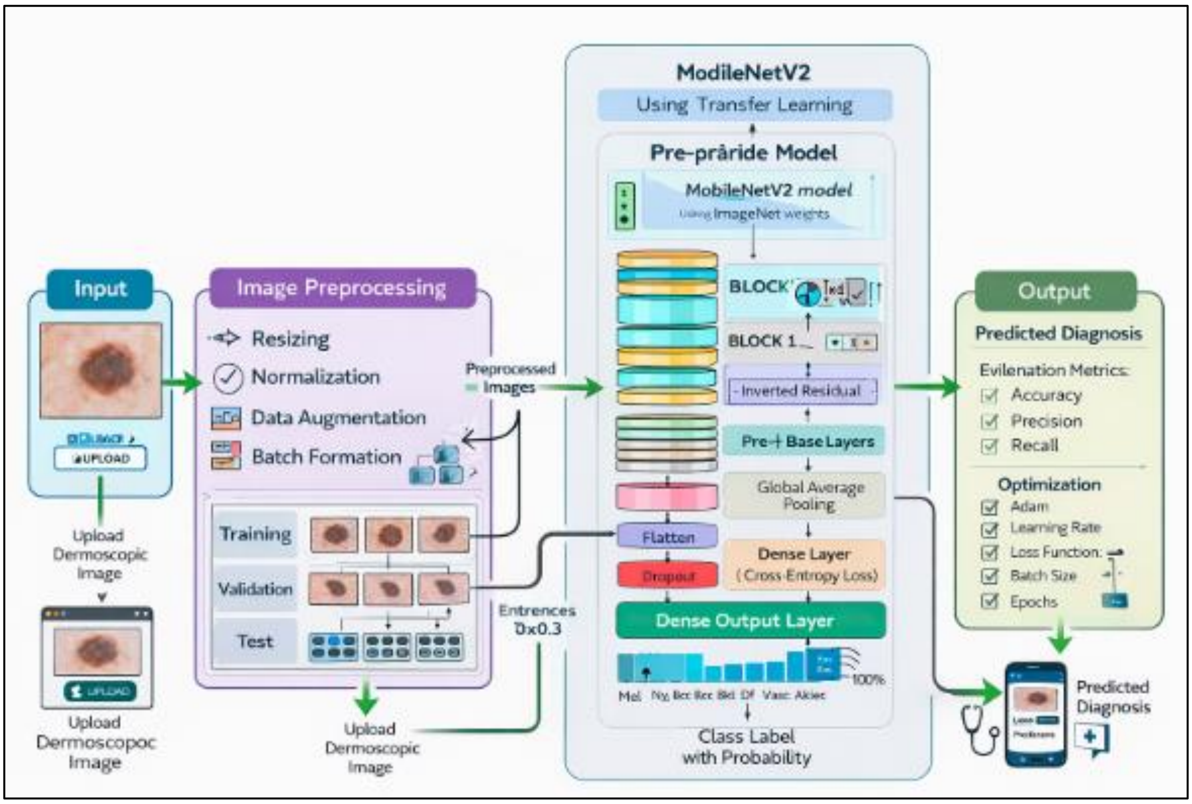

Fig 1 Architecture of the Proposed Skin Cancer Detection Model

A. Implementation Details

➢ *Development Environment*

The skin cancer detection system was developed primarily in Python 3.x. A deep learning model was constructed employing TensorFlow 2.x alongside the Keras API to facilitate advanced neural network architectures.

- *The Implementation Environment Included the Following Components:*

✓ Integrated Development Environment (IDE): Visual Studio Code and Jupyter Notebook
✓ Core Frameworks: TensorFlow and Keras
✓ Supporting Libraries: NumPy, Pandas, Matplotlib, and Scikit-learn
✓ Web Development Framework: Flask
✓ Platform: Windows 10 operating system
✓ Computational Setup: Intel i5 CPU paired with 8 GB of RAM (with optional GPU support)

➢ *Data Preparation and Preprocessing*

This system leverages the HAM10000 dataset, comprising 10,015 dermoscopic images classified across seven distinct categories of skin lesions.

- Train-test split ratio (80:20)
- Image resizing
- Normalization
- Data augmentation

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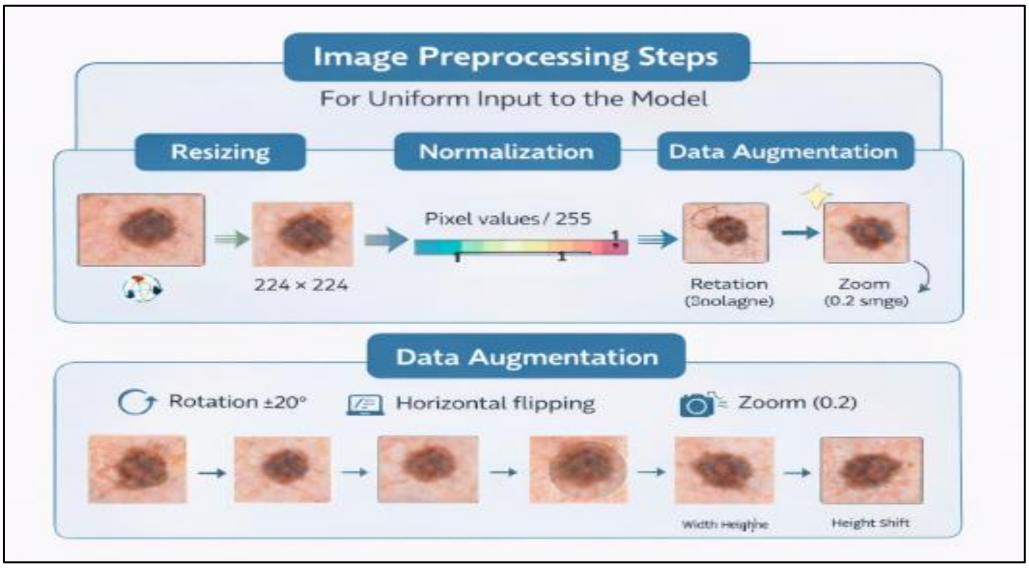

Fig 2 Data Preparation and Preprocessing

➢ *Model Architecture Implementation*

The model architecture was implemented using transfer learning with the MobileNetV2 backbone.

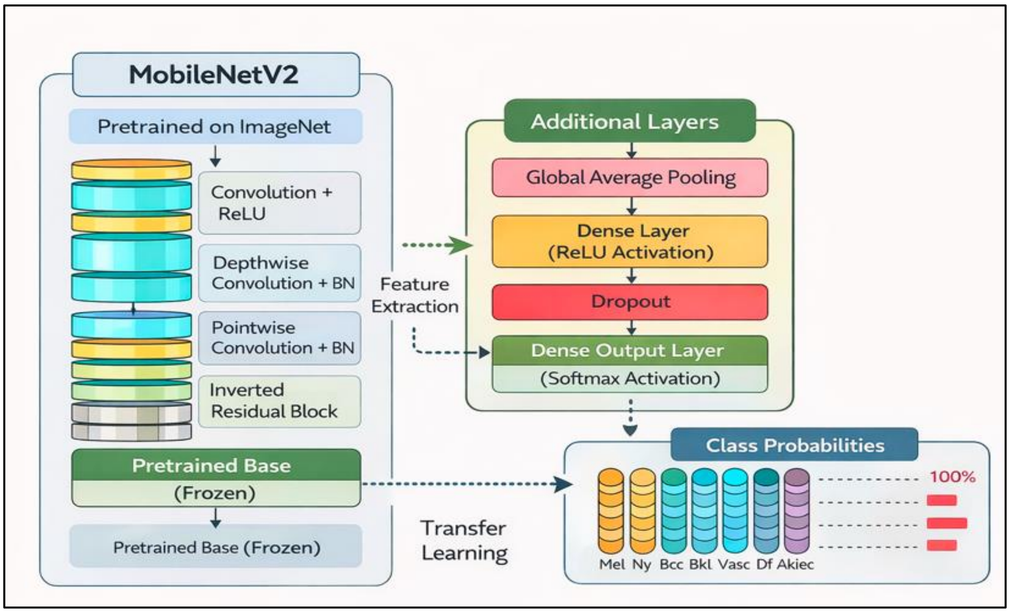

Fig 3 MobileNetV2 Architecture with Transfer Learning

Transfer learning is applied using pretrained ImageNet weights. The base layers are frozen initially, and custom classification layers are added:

- Global Average Pooling
- Dense layer (ReLU activation)
- Dropout layer
- Final Dense layer with Softmax activation

➢ *Training Strategy*

The model was compiled using:

- Optimizer: Adam
- Learning Rate: 0.0001
- Loss Function: Categorical Cross-Entropy
- Metrics: Accuracy

The categorical cross-entropy loss function is defined as:

$$Loss = \sum_{j=1}^{n} y \log(\hat{y})$$

➢ *Training Configuration:*

- Batch Size: 16
- Epochs: 10
- Validation Data: 20% split

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/26apr1616

During training, model weights were updated using backpropagation and gradient descent optimization.

Transfer learning reduced training time significantly while maintaining feature quality.

➢ *Model Evaluation*

Following the training phase, performance assessment of the model was conducted on the validation dataset employing the subsequent metrics:

- Accuracy: 71.38%
- Precision: 85.77%
- Recall: 60.42%

Table 1 Model Comparison Table

Model	Accuracy (%)
Support Vector Machine (SVM)	65%
Basic CNN Model	68%
Proposed MobileNetV2	**71.38%**

The proposed MobileNetV2 model outperforms traditional SVM and basic CNN approaches in terms of classification accuracy. This improvement demonstrates the effectiveness of transfer learning and depthwise separable convolutions in medical image classification.

➢ *Confusion Matrix:*

A confusion matrix was constructed to evaluate the model's class-specific predictive accuracy. This visualization enabled the identification of key performance patterns across individual categories.

- Misclassified lesion types
- Class imbalance effects
- Model sensitivity per class

Precision quantifies the accuracy of a model's positive classifications, whereas recall evaluates its capacity to identify every true positive instance.

➢ *Deployment Using Flask*

To facilitate immediate operational use, the trained neural network was hosted via the Flask web application framework.

➢ *Deployment Process:*

- The trained model was saved in .h5 format.
- A Flask server was created with prediction API endpoints.
- Users upload dermoscopic images through a web interface.
- The image undergoes preprocessing (resizing + normalization).
- The model predicts the class label.
- The predicted class and probability score are displayed.

This deployment allows accessible and user-friendly skin lesion analysis.

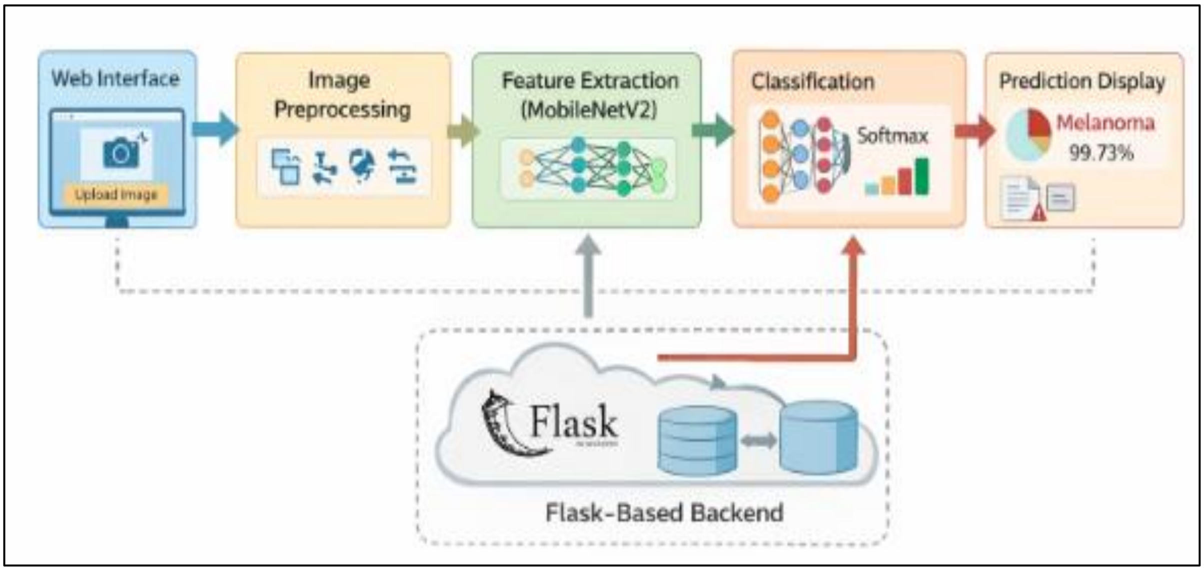

Fig 4 Flask-Based Deployment Architecture

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/26apr1616

IV. RESULTS AND DISCUSSION

The efficacy of the proposed skin cancer classification framework was assessed through conventional performance indicators, namely accuracy, precision, and recall. Training and validation employed dermoscopic imagery sourced from the HAM10000 dataset, enabling the differentiation of seven distinct skin lesion categories.

The architecture incorporating MobileNetV2 attained a comprehensive accuracy of 71.38%, complemented by a precision score of 85.77% and a recall of 60.42%. The elevated precision underscores the model's capacity to deliver dependable identifications for targeted lesion categories. Nevertheless, the comparatively lower recall highlights challenges in detecting all true positives, attributable largely to class imbalance within the dataset and morphological resemblances among lesion variants.

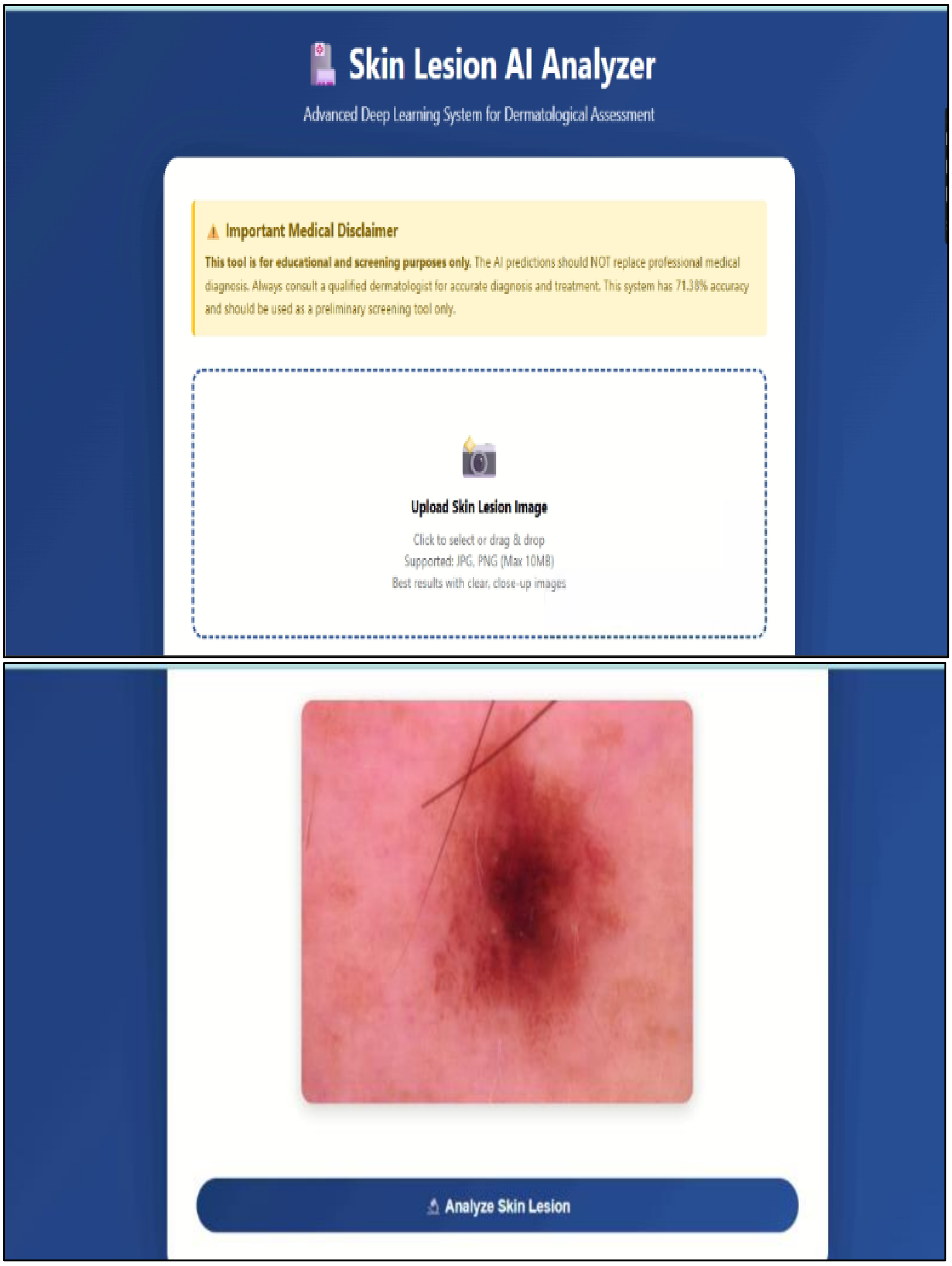

Fig 5 Skin Lesion AI Analyzer

➢ *Web Application Interface*

- Users can upload a skin lesion image using the upload section in the center.
- The system supports JPG and PNG formats (maximum 10MB).
- After uploading, the image is analyzed by the model.
- The prediction result is displayed on the screen.
- A medical disclaimer is shown at the top of the page.

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/26apr1616

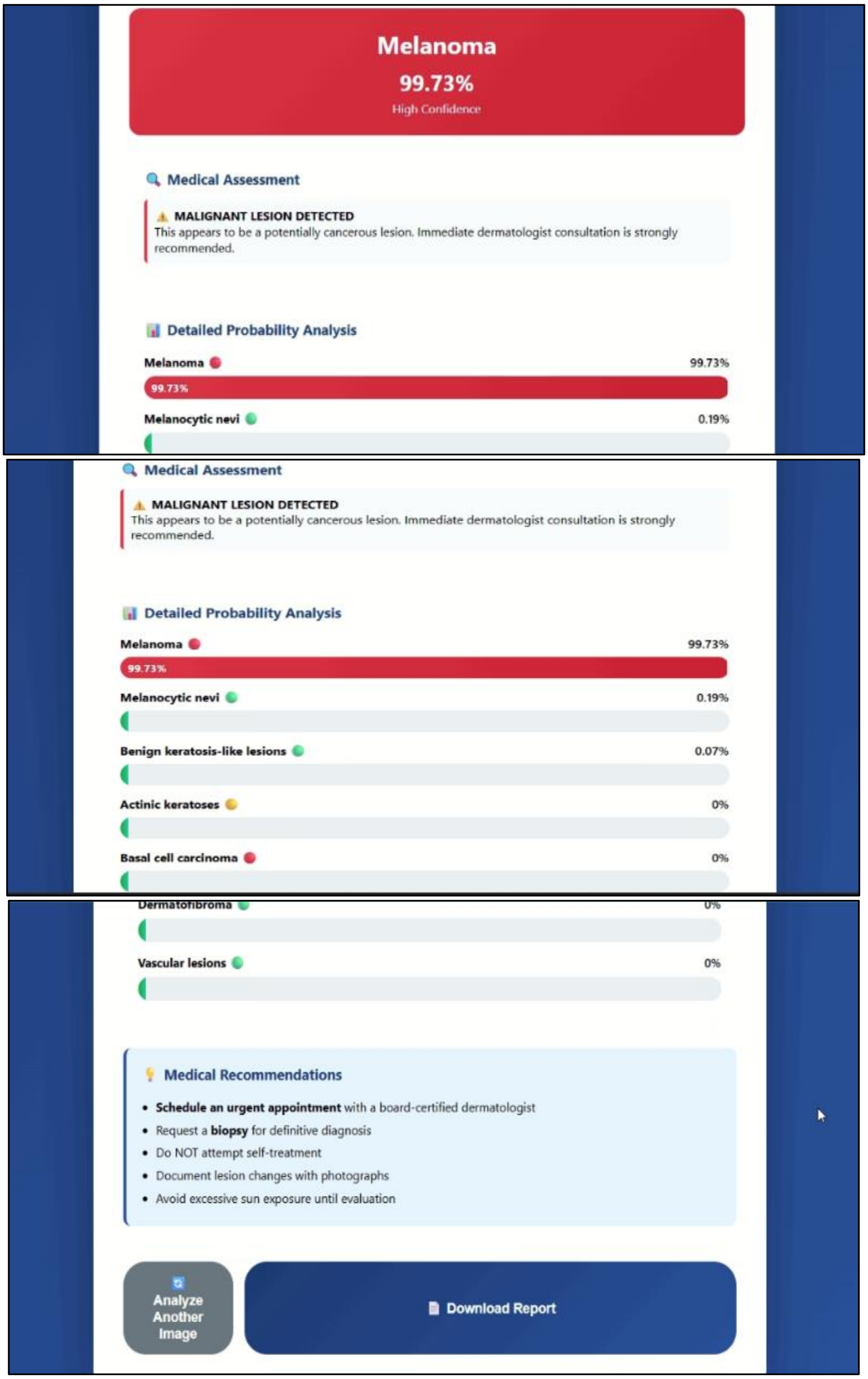

Fig 6 Web Application Interface

➢ *Prediction Result and Probability Analysis*

- The final prediction result generated by the system.
- The model detected a malignant lesion.
- The predicted class (Melanoma) shows the highest probability (99.73%).
- A detailed probability analysis is displayed for all lesion categories.
- Each class is shown with its corresponding confidence percentage.
- This helps in understanding how strongly the model supports the predicted result.

International Journal of Innovative Science and Research Technology
ISSN No: -2456-2165
https://doi.org/10.38124/ijisrt/26apr1616

➢ *Generated Skin Lesion AI Analysis Report*

- The automatically generated analysis report.
- The report includes the date and time of analysis.
- The system name and overall model accuracy (71.38%) are mentioned.
- The predicted condition (Melanoma) is displayed with confidence level (99.73%).
- A complete probability breakdown of all lesion classes is provided.
- A medical disclaimer is included for ethical and professional compliance.
- The report confirms that the system can generate structured diagnostic summaries.

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SKIN LESION AI ANALYSIS REPORT
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Date: 2/11/2026, 10:55:09 AM
System: Skin Cancer Detection AI (71.38% Accuracy)

ANALYSIS RESULTS:
Predicted Condition: Melanoma
Confidence Level: 99.73%

PROBABILITY BREAKDOWN:
Melanoma: 99.73%
Melanocytic nevi: 0.19%
Benign keratosis-like lesions: 0.07%
Actinic keratoses: 0%
Basal cell carcinoma: 0%
Dermatofibroma: 0%
Vascular lesions: 0%

DISCLAIMER:
This AI analysis is for screening purposes only and should NOT replace
professional medical diagnosis. Please consult a qualified dermatologist
for accurate diagnosis and treatment recommendations.

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Generated by Skin Lesion AI Analyzer
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V. CONCLUSION

This research introduces an artificial intelligence framework employing deep neural networks for identifying skin malignancies, utilizing the MobileNetV2 model enhanced through transfer learning techniques. Training occurred on the HAM10000 image collection to distinguish among seven distinct categories of dermatological abnormalities. The framework attained a classification precision of 71.38%, underscoring the efficacy of compact CNN models in medical imaging tasks. Techniques such as image enhancement and synthetic data expansion bolstered the framework's robustness and efficacy. Furthermore, a web interface constructed with Flask enables seamless real-time deployment, delivering rapid automated assessments ideal for preliminary screening in dermatological practice. While not a substitute for expert clinical evaluation, this tool supports healthcare professionals by offering initial insights and broadening access to intelligent diagnostic aids.

VI. FUTURE SCOPE

Future enhancements to the system could involve expanding the training dataset and addressing class imbalance to boost model performance and recall rates. Additionally, optimizing the deeper layers of the MobileNetV2 architecture through fine-tuning holds potential for elevating classification precision.

Subsequent research may evaluate state-of-the-art models, including EfficientNet and ResNet variants, against the existing framework to attain superior outcomes. Incorporating interpretability methods, such as Grad-CAM, would allow visualization of salient image features driving the model's decisions.

Moreover, deploying the system on mobile platforms or cloud infrastructure could facilitate instantaneous skin cancer detection, particularly in underserved rural and remote healthcare settings.

VII. LIMITATIONS

Although the developed system yields favorable outcomes, it is subject to several constraints. Its efficacy relies substantially on the dataset's quality and distributional equity. Imbalances among classes in the HAM10000 dataset could compromise the model's sensitivity toward less prevalent lesion categories. Disparities in imaging attributes—such as quality, illumination, and resolution—

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/26apr1616

may impair predictive performance. Training occurred over a constrained set of iterations, potentially hindering complete convergence. Furthermore, this framework serves solely as an auxiliary aid for preliminary screening and must not supplant expert clinical evaluation. Deployment in practical settings necessitates rigorous validation using expanded, heterogeneous datasets.

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