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Skin lesion classification for Melanoma Detection using deep learning

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Abstract:
Melanoma is a highly aggressive skin cancer where early and accurate diagnosis is critical for improving patient survival. Traditional diagnostic methods rely on visual assessment and are often subjective and inconsistent, creating a need for reliable automated solutions.
This study proposes a deep learning-based skin lesion classification system using Convolutional Neural Networks (CNNs) trained on dermoscopic images. The model automatically learns discriminative features, reducing dependence on manual feature extraction and minimizing human bias. To enhance performance and generalization, preprocessing techniques such as normalization, data augmentation (flipping, rotation, scaling), and noise reduction are applied.
The system is evaluated using accuracy, precision, recall, and F1-score, demonstrating strong diagnostic performance in melanoma detection. Overall, the study highlights the potential of deep learning to support clinical decision-making and improve early diagnosis, leading to better patient outcomes.

Keywords: Melanoma Detection, Deep Learning, Convolutional Neural Networks (CNN), Skin Lesion Classification, Dermoscopic Image Analysis.

I. INTRODUCTION

Melanoma is one of the most aggressive and dangerous types of cancer, where early detection significantly improves survival rates. However, it is difficult to distinguish from benign skin lesions, often leading to misdiagnosis and delayed treatment. Traditional diagnostic methods such as clinical examination, dermoscopy, and biopsy are effective but subjective, time-consuming, and dependent on the expertise of dermatologists, resulting in variability in diagnosis.
Recent advancements in artificial intelligence, particularly deep learning, have introduced powerful solutions for medical image analysis. Convolutional Neural Networks (CNNs) can automatically learn important visual features, making them highly effective for melanoma detection. The HAM10000 dataset, containing 10,015 dermoscopic images across seven skin lesion categories, provides a strong foundation for developing accurate classification models to support clinical decision-making and improve diagnostic accuracy.

A. Research Problem

Melanoma detection remains challenging due to its visual similarity with benign skin lesions, making accurate early diagnosis difficult for both dermatologists and automated systems. Differences in color, texture, and shape are often subtle, increasing the risk of misclassification.
Another major issue is dataset imbalance, as melanoma cases are fewer than benign ones, leading models to be biased toward non-cancerous predictions and reducing sensitivity to malignant cases. Additionally, variations in imaging conditions (lighting, resolution, skin tone, and artifacts like hair or shadows) introduce noise and reduce model reliability.

Finally, many models lack generalizability, performing well in controlled environments but failing in real-world clinical settings. This highlights the need for more robust, unbiased, and clinically applicable melanoma detection systems.

B. Problem Statement

Skin cancer, particularly melanoma, is one of the most dangerous cancers, where early detection is crucial for improving survival rates. However, melanoma closely resembles benign skin lesions, making accurate diagnosis difficult even for experienced dermatologists. Traditional methods such as clinical examination, dermoscopy, and biopsy are effective but subjective, time-consuming, and dependent on expertise, leading to inconsistent outcomes.

Limited access to skilled dermatologists and advanced diagnostic tools further delays diagnosis, especially in many regions, reducing treatment effectiveness. Although deep learning, especially CNNs, offers promising solutions through automated feature extraction, challenges such as dataset imbalance, poor generalization, and lack of explainability still remain.

Therefore, there is a need for an accurate, reliable, and scalable deep learning-based system for melanoma detection. Such a system can assist clinicians, reduce diagnostic errors, enable early treatment, and improve overall patient outcomes.

C. Research Gaps

A key research gap is the lack of model generalization, as melanoma detection systems often fail to perform well on new datasets and varying imaging conditions. This can be addressed using data augmentation, transfer learning, and domain adaptation to improve robustness in real-world scenarios. Another major challenge is dataset imbalance, where melanoma cases are underrepresented compared to benign lesions, leading to biased predictions. Techniques such as oversampling (SMOTE), class weighting, and focal loss can help improve sensitivity toward minority classes.

Additionally, clinical integration remains a challenge due to regulatory barriers, hardware limitations, and lack of clinician trust, which can be overcome by developing lightweight, real-time models and validating them through clinical trials. Finally, there is a trade-off between binary and multiclass classification, where binary models offer better melanoma sensitivity, while multiclass models provide broader diagnostic insights. A hybrid approach can balance both accuracy and clinical usefulness.

II. LITERATURE REVIEW

Ashfaq et al. (2025) reviewed AI-based melanoma diagnosis, highlighting the effectiveness of CNNs and multimodal approaches that combine images with clinical data, achieving higher accuracy than dermatologists in controlled settings. The study emphasizes the need for explainability and trust, while limitations include dataset bias, lack of interpretability, and challenges in real-world clinical integration.

Thwin & Park (2024) applied CNN-based deep learning models with preprocessing, augmentation, and transfer learning to improve skin cancer detection accuracy. The study demonstrated strong classification performance, but highlighted issues such as dataset imbalance, image variability, and limited applicability in real-world clinical environments.

Shakya et al. (2024) proposed a multimodal deep learning framework combining dermoscopic images with patient metadata, improving accuracy from 89.2% to 93.5%. The approach enhances diagnostic reliability but faces challenges related to dataset bias, complexity, and lack of interpretability for clinical adoption.

Khan et al. (2024) developed a multiclass classification system using feature fusion and hybrid optimization techniques, achieving 89% accuracy. The method improves classification performance but suffers from high computational cost, dataset imbalance, and limited generalization to real-world scenarios.

Moturi et al. (2024) compared CNN architectures for melanoma detection and achieved up to 95% validation accuracy, integrating the model into a web-based system for real-time predictions. Despite strong performance, the system showed limited generalization and was affected by dataset imbalance and image variability.

Ornek et al. (2024) combined deep learning feature extraction with machine learning classifiers, where ANN achieved the highest accuracy of 71.8%. While the study shows the potential of hybrid approaches, performance remains moderate due to limited dataset diversity and relatively simple preprocessing methods.

Bishnu et al. (2024) evaluated multiple transfer learning models, with VGG19 achieving the highest accuracy of 93.05% in skin lesion classification. The study highlights improved generalization through transfer learning but notes limitations such as dataset dependency, imbalance, and lack of model interpretability.

Khan et al. (2024) compared several CNN architectures for melanoma detection, with ResNet50 achieving the best accuracy of 95.6%. The study demonstrates the effectiveness of transfer learning but faces challenges related to interpretability, computational cost, and reliance on single datasets.

Akram et al. (2023) proposed a hybrid framework combining U-Net segmentation with CNN-based classification, achieving over 92% accuracy and improved lesion detection. However, the system is computationally expensive and affected by dataset imbalance and segmentation errors.

Uma & Sushama (2024) used CNN and transfer learning for skin disease classification, showing improved diagnostic accuracy and reduced reliance on manual analysis. Challenges include dataset imbalance, image artifacts, and limited generalization in real-world clinical settings.

Shetty et al. (2022) developed a CNN-based melanoma detection system achieving 90.3% accuracy, comparable to dermatologists. While promising, the model is limited by dataset bias, generalization issues, and lack of explainability for clinical use.

Liu et al. (2025) proposed an ensemble deep learning approach that improved accuracy, precision, recall, and F1-score compared to single models. Despite improved reliability, the approach suffers from high computational complexity and dataset imbalance challenges.

Wu et al. (2022) reviewed AI techniques in melanoma diagnosis, emphasizing CNN superiority and improved performance with metadata integration. However, challenges include dataset imbalance, ethical concerns, and lack of interpretability in clinical applications.

Hatem (2022) proposed a KNN-based skin lesion classification system achieving 98% accuracy for binary classification. Although simple and effective, it suffers from scalability issues, noise sensitivity, and inability to handle multiclass problems.

Lu & Zadeh (2022) applied XceptionNet for melanoma detection, achieving 87.42% accuracy with good precision and recall. Limitations include small dataset size, lack of diversity, and interpretability issues in clinical settings.

Kumar & Gupta (2022) combined U-Net segmentation with transfer learning, achieving up to 93% accuracy in classification tasks. The approach improves detection but is limited by dataset diversity, over-reliance on pre-trained models, and lack of explainability.

Bhatt et al. (2023) reviewed machine learning and deep learning techniques, concluding that CNNs outperform traditional methods in melanoma detection. However, issues such as dataset imbalance, image variability, and lack of interpretability remain unresolved.

Devaraneni (2023) applied CNN and transfer learning models like VGG16, achieving up to 92% accuracy in classification. Despite strong performance, challenges include small datasets, computational cost, and limited real-world generalization.

Abir et al. (2024) used CNN-based models for skin lesion classification, achieving reliable performance and reduced misclassification. However, dataset imbalance, image variability, and generalization issues still affect model robustness.

Brinker et al. (2019) demonstrated that CNN models can achieve dermatologist-level accuracy in melanoma detection and improve diagnostic consistency. However, limitations include dataset bias, lack of transparency, and regulatory challenges for clinical adoption.

III. PROPOSED FLOW OF THE RESEARCH

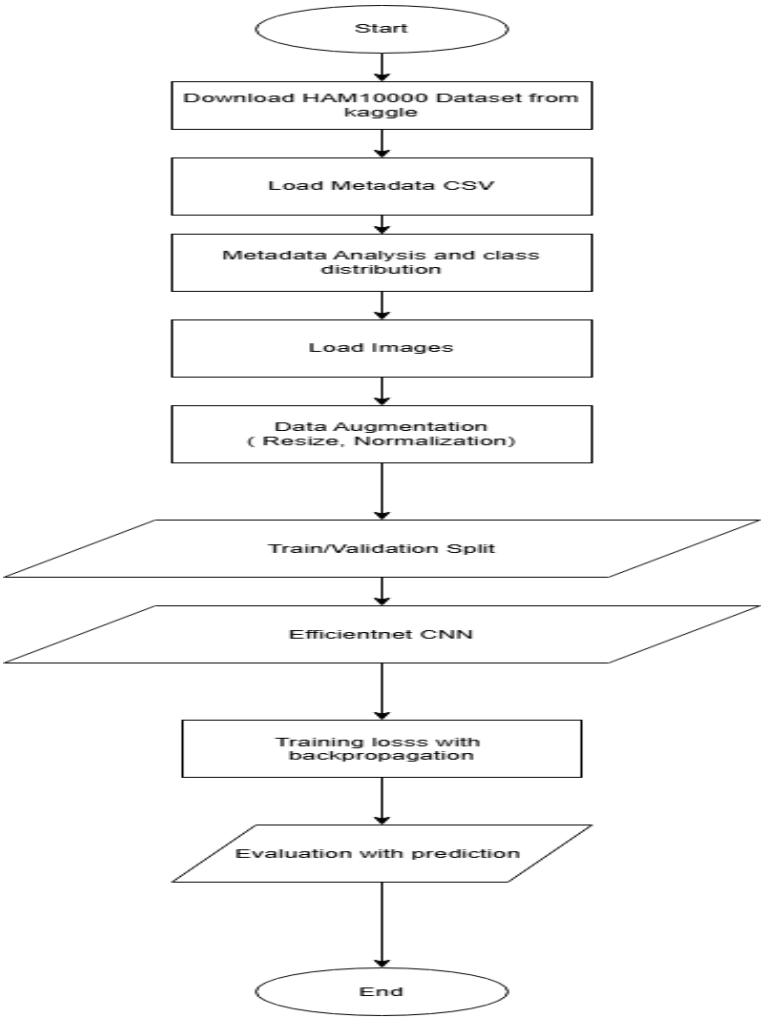

Fig 1: Proposed Flow of the Research

The proposed system presents a smart and scalable deep learning-based pipeline for automated skin lesion classification. The process begins with dermoscopic images as input, which are then prepared through preprocessing techniques to ensure consistency and improve model performance. Images are resized to a fixed dimension, normalized for stable training, and enhanced using augmentation methods such as rotation, flipping, and scaling to increase dataset diversity and reduce overfitting. Label encoding is also applied to convert categorical outputs into machine-readable formats.

Following preprocessing, the augmented dataset is used to improve model generalization, particularly in handling limited and imbalanced medical data. The processed images are then fed into EfficientNet, a high-performance convolutional neural network that uses transfer learning to extract complex visual features. By leveraging pre-trained weights, the model improves accuracy while reducing training time and computational cost.

The model undergoes training and validation phases, where it learns to classify skin lesions based on extracted features while preventing overfitting. Performance is evaluated using standard metrics, and the system generates outputs including predicted lesion type and confidence scores, along with a detailed classification report for analysis.

The study utilizes the HAM10000 dataset, a widely used benchmark containing 10,015 dermoscopic images across seven skin lesion classes. The dataset is highly imbalanced, with melanocytic nevi dominating (66.94%) and melanoma representing only 11.11%, highlighting a key challenge in model training and evaluation.

In addition to image data, the dataset includes metadata such as lesion ID, diagnosis type, patient age, sex, and lesion location, providing valuable clinical context. This combination of visual and patient-level information supports more comprehensive analysis and improves the potential for accurate and reliable skin lesion classification.

IV. IMPLEMENTATION

A. Dataset

The performance of a deep learning model largely depends on the quality and diversity of the dataset used for training. In this study, the HAM10000 (Human Against Machine with 10,000 images) dataset is utilized, which is widely recognized in dermatological image analysis. It contains dermoscopic images of common pigmented skin lesions, making it suitable for skin cancer classification tasks.

The dataset consists of 10,015 high-resolution dermoscopic images categorized into seven different skin lesion classes, collected from diverse populations and imaging sources to ensure variability. Along with images, it also provides valuable metadata such as lesion type, patient age, gender, and lesion location, enabling more comprehensive analysis.

The dataset was obtained from Kaggle using the KaggleHub API, allowing efficient downloading and integration into the workflow. Metadata is accessed in CSV format for further processing and analysis, supporting both image-based and clinical feature-based modeling.

B. Dataset Description

The HAM10000 dataset is a widely used benchmark in skin lesion analysis, consisting of dermoscopic images and a metadata file. It provides both visual and contextual information, making it suitable for developing machine learning models for skin disease classification.

The dataset includes 10,015 high-quality dermoscopic images categorized into seven classes: akiec, bcc, bkl, df, mel, nv, and vasc. These classes cover both benign and malignant lesions, enabling the development of robust classification models for accurate diagnosis.

In addition to images, the dataset contains a metadata file (HAM10000_metadata.csv) with important attributes such as lesion ID, image ID, diagnosis type, diagnostic method, patient age, gender, and lesion location. This information enhances analysis by incorporating clinical context alongside image data.

Exploratory data analysis using functions like metadata.info() helps understand dataset structure, data types, and missing values, ensuring proper preprocessing before model training.

Overall, the HAM10000 dataset provides a rich combination of image and metadata information, making it highly effective for building accurate and reliable skin lesion classification systems.

C. Data Analysis and Visualization

Before training the deep learning model, detailed analysis of the HAM10000 dataset is performed to understand its characteristics and identify potential challenges. A key observation is the presence of class imbalance, where certain lesion types have significantly more samples than others. Melanocytic nevi (nv) dominate the dataset with around 6,700 samples, followed by melanoma (mel) and benign keratosis-like lesions (bkl) with approximately 1,100 samples each. Other classes such as basal cell carcinoma (bcc), actinic keratoses (akiec), dermatofibroma (df), and vascular lesions (vasc) have comparatively fewer samples, with df and vasc being the least represented. This imbalance can bias the model toward majority classes and reduce its ability to accurately detect clinically important minority classes like melanoma.

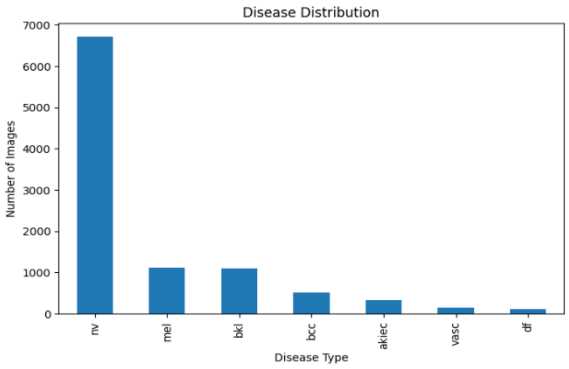

Fig 2: Disease Distribution

Exploratory Data Analysis (EDA) is conducted to examine patterns in lesion types, patient demographics, and anatomical locations. Visualization techniques such as bar plots, histograms, and box plots are used to analyze class distribution, age variation, and potential outliers.

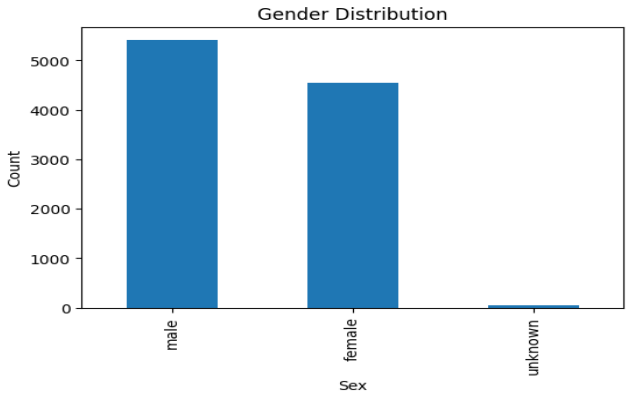

Fig 3: Gender Distribution

The gender distribution shows approximately 5,400 male and 4,500 female samples, with minimal unknown values, indicating a relatively balanced representation that helps reduce demographic bias in model training.

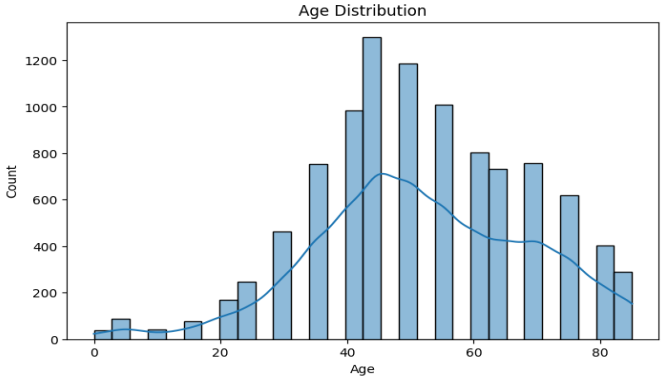

Fig 4: Age Distribution

Age distribution ranges from 0 to 85 years, with most cases concentrated between 40 and 70 years, especially around 45–60 years, aligning with clinical observations that skin lesions are more common in middle-aged and older individuals.

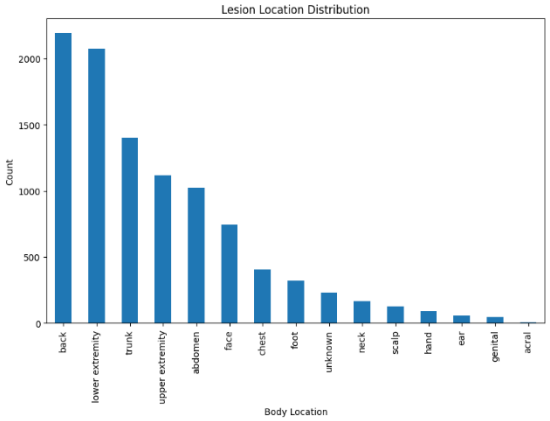

Fig 5: Lesion Location Distribution

Analysis of lesion location reveals that most samples are from the back (~2,200) and lower extremities (~2,100), followed by trunk, upper extremities, and abdomen. Other regions such as face, neck, scalp, and

acral areas have fewer samples, indicating uneven anatomical distribution. This variation reflects real-world patterns influenced by sun exposure and clinical examination focus.

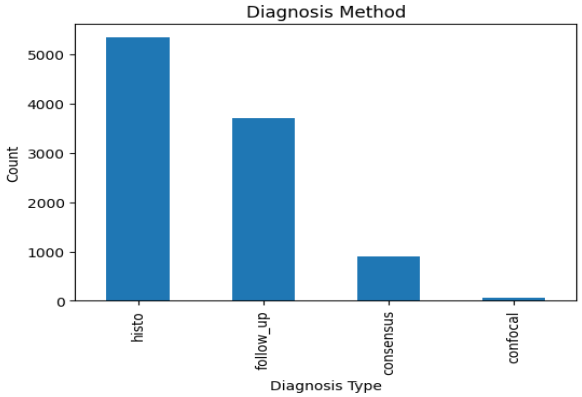

Fig 6: Diagnosis method

Additionally, diagnostic methods in the dataset include histopathology (~5,300 samples), follow-up (~3,700), expert consensus (~900), and confocal microscopy (least used). The dominance of histopathology, considered the gold standard, ensures high reliability of labels used for training.

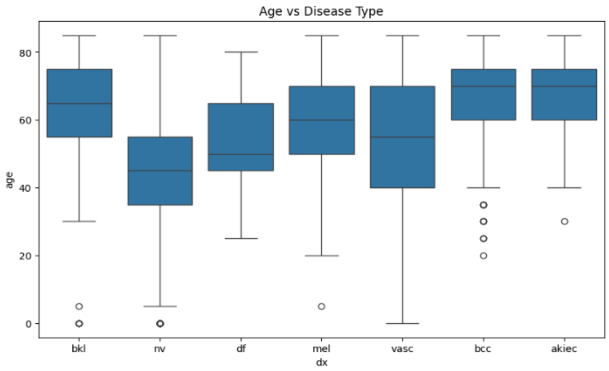

Fig 7: Age vs Disease Type

Further analysis shows relationships between age and disease type, where conditions like basal cell carcinoma (bcc) and actinic keratoses (akiec) are more common in older patients, while melanoma is frequent in the 50–70 age range. Melanocytic nevi (nv) appear across a wider age group.

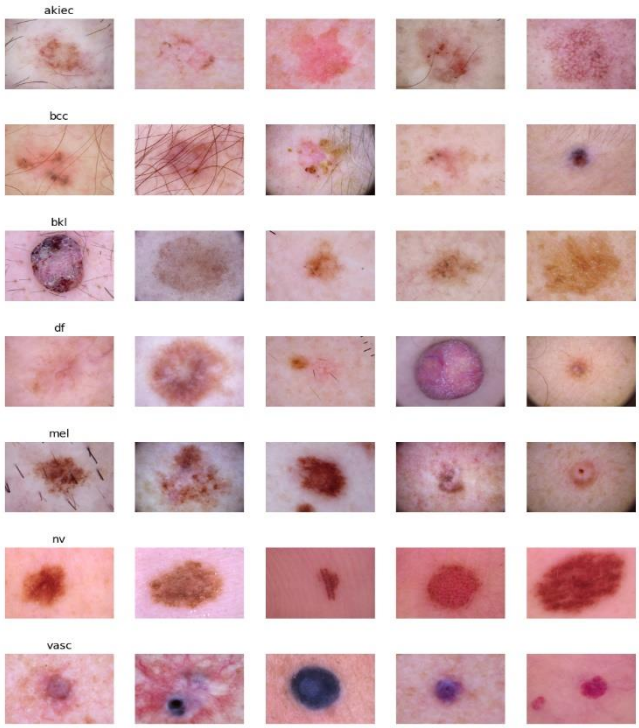

Fig 8: lesion classes

Visualization of sample images highlights distinct visual patterns among lesion types, such as irregular borders and pigmentation in melanoma, symmetry in nevi, and color variations in vascular lesions. These features are critical for CNN models, which rely on texture, shape, and color differences for classification. Overall, the dataset analysis reveals important insights including class imbalance, demographic distribution, anatomical variation, and reliable diagnostic labeling. These findings guide preprocessing strategies such as augmentation and class balancing, ensuring the development of a robust and accurate deep learning model for skin lesion classification and melanoma detection.

D. Data Preprocessing

The HAM10000 dataset was preprocessed through a structured pipeline to ensure that both image data and metadata were clean, consistent, and suitable for deep learning. Preprocessing is a critical stage that directly impacts model performance, stability, and generalization. Initially, missing values in metadata fields such as age, gender, and lesion location were identified using exploratory checks and handled appropriately. Numerical values like age were filled using mean values, while categorical fields were assigned default labels such as “unknown,” ensuring no loss of data and maintaining dataset consistency. To enable proper data handling, image paths were mapped by linking metadata image identifiers with actual file locations from multiple directories. This ensured that each record was correctly associated with its corresponding image, allowing smooth data loading during training. Label encoding was then applied to convert categorical diagnosis labels into numerical form, enabling compatibility with deep learning models. Each lesion class was assigned a unique integer value, allowing the model to effectively learn and differentiate between categories.

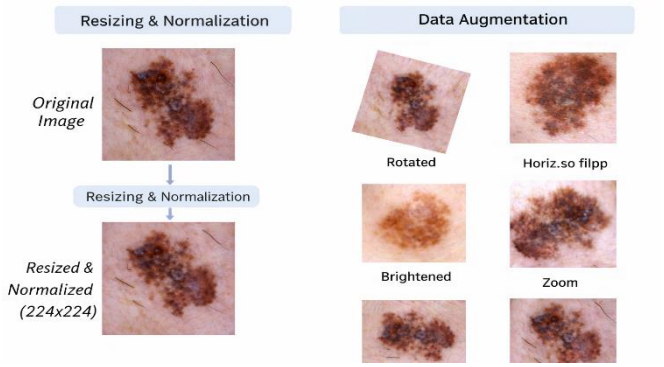

Fig 9: Outcome of Resizing and Normalization as well Data Augmentation

Since images in the dataset varied in size and resolution, all images were resized to a uniform dimension of 224×224 pixels to meet CNN input requirements. Pixel normalization was applied by scaling values from 0–255 to 0–1, which improves training stability, accelerates convergence, and prevents numerical instability. The dataset was then split into training and testing sets using an 80:20 ratio with stratified sampling to preserve class distribution, ensuring unbiased evaluation and better generalization.

To further enhance model performance and address dataset imbalance, data augmentation techniques were applied. Transformations such as rotation, flipping, zooming, shifting, and brightness adjustments were used to artificially increase dataset diversity. These techniques help the model learn robust patterns under varying conditions, reduce overfitting, and improve real-world applicability.

Overall, the preprocessing pipeline transforms raw dermoscopic images into a standardized and enriched dataset by combining resizing, normalization, label encoding, and augmentation. This ensures that the deep learning model can effectively learn meaningful features, resulting in improved accuracy, reliability, and generalization in skin lesion classification and melanoma detection.

V. RESULTS AND OBSERVATIONS

The EfficientNetB0 model was evaluated after training on the HAM10000 dataset to classify dermoscopic images into seven skin lesion categories. The model learned important visual features such as texture, irregular borders, asymmetry, and color variations, which are essential for distinguishing between benign and malignant lesions. Training was performed using the Adam optimizer with categorical cross-entropy loss, while both training and validation datasets were used to monitor performance and ensure proper generalization. Key metrics tracked during training included accuracy and loss across epochs.

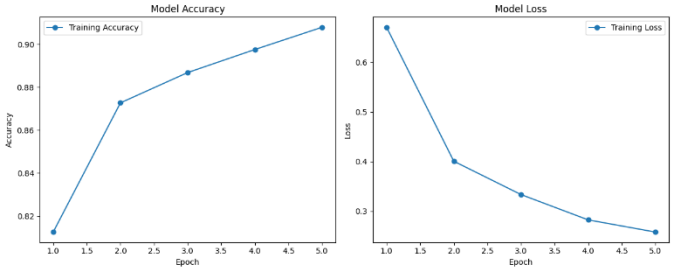

Fig: Loss vs Epochs graph in terms of training vs validation loss

The accuracy analysis shows a steady improvement in both training and validation accuracy, indicating effective learning. Training accuracy increased from approximately 81% to 91%, while training loss decreased from around 0.67 to 0.26, demonstrating consistent convergence. The close trend between training and validation accuracy suggests minimal overfitting and good generalization to unseen data. Loss

analysis further confirms this, as both training and validation loss decrease steadily, indicating that the model is effectively minimizing prediction errors and learning meaningful patterns from the data.
Table: 1 Class-wise Performance**.**

Class	Precision	Recall	F1-score	Support
akiec	0.78	0.72	0.75	65
bcc	0.84	0.81	0.82	103
bkl	0.85	0.83	0.84	220
df	0.80	0.76	0.78	23
mel	0.86	0.82	0.84	223
nv	0.93	0.96	0.94	1341
vasc	0.90	0.87	0.88	28

The classification report provides detailed performance for each class using precision, recall, and F1-score. The model achieved strong results for most classes, particularly melanocytic nevi (nv) with precision 0.93, recall 0.96, and F1-score 0.94 (1341 samples), and melanoma (mel) with precision 0.86, recall 0.82, and F1-score 0.84 (223 samples). Other classes such as bcc and bkl also showed good performance, while minority classes like dermatofibroma (df) and vascular lesions (vasc) had slightly lower scores due to limited data. These metrics highlight the model's reliability, especially in clinically important melanoma detection.

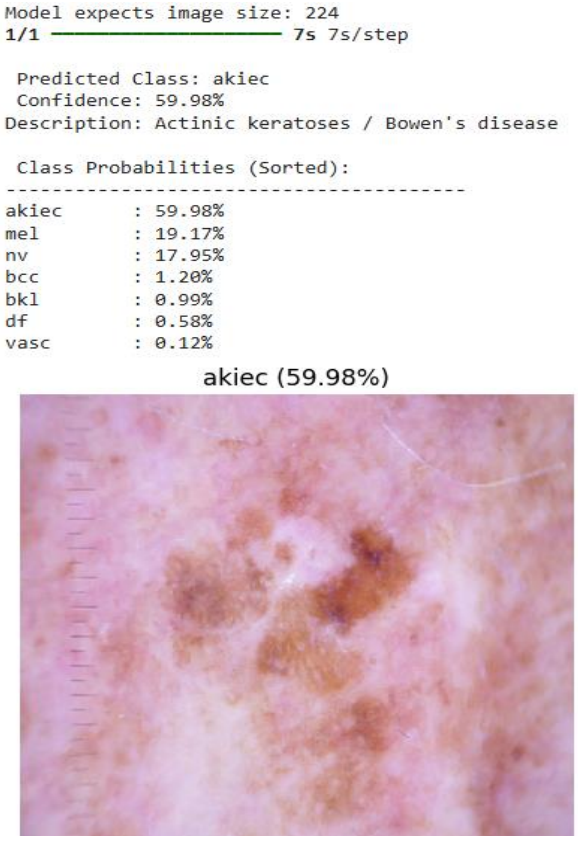

Fig: Testing with probabilities

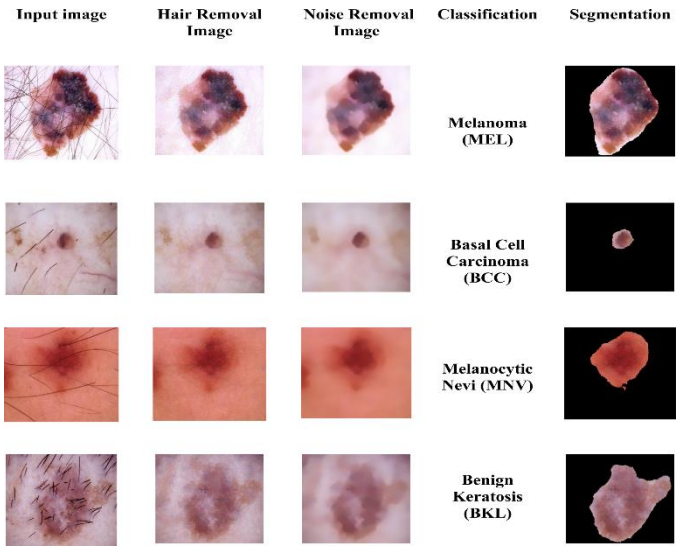

Fig: Classification results of EfficientNetB0 model

The model achieved an overall accuracy of approximately 90%, outperforming traditional CNN (85%) and ResNet50 (88%) models. EfficientNetB0 proved more effective due to its balanced scaling and strong feature extraction capabilities. Data augmentation further improved generalization by introducing variations in orientation, brightness, and scale, reducing overfitting. Example predictions show that the model can classify lesions with reasonable confidence, though overlapping probabilities among similar classes indicate the need for clinical validation in certain cases.

Table: 2 Model Comparison

Model	**Accuracy**
CNN	85%
ResNet50	88%
EfficientNetB0	90%

Overall, the evaluation demonstrates that the EfficientNetB0-based system provides accurate, reliable, and scalable skin lesion classification. The combination of transfer learning, preprocessing, and augmentation enables strong performance, making the model a promising tool for assisting dermatologists in early melanoma detection and improving diagnostic efficiency.

VI. CONCLUSIONS

This study developed an intelligent and automated skin lesion classification system using deep learning, with a focus on early melanoma detection. Traditional diagnostic methods are often subjective, time-consuming, and dependent on expert knowledge, highlighting the need for reliable automated solutions. Key challenges identified include poor model generalization across real-world conditions, dataset imbalance with fewer melanoma samples, lack of clinical integration, and visual similarity between benign and malignant lesions.

To address these issues, the study proposed a deep learning framework based on EfficientNetB0 with transfer learning. A comprehensive preprocessing pipeline, including resizing, normalization, and data augmentation, was implemented to improve dataset quality and reduce overfitting. Stratified data splitting and augmentation techniques helped mitigate class imbalance and enhance model generalization.

The model achieved strong performance on the HAM10000 dataset, reaching approximately 90% accuracy and outperforming traditional CNN and ResNet50 models. High precision and recall, particularly

for melanoma, demonstrate its effectiveness in detecting clinically important cases. The model successfully learned key visual features such as texture, asymmetry, and color variations, which are critical for accurate diagnosis.

Overall, the proposed system provides an efficient, scalable, and reliable solution for automated skin lesion classification. With further improvements such as multimodal data integration and clinical validation, it has strong potential to support dermatologists, enable early diagnosis, and improve patient outcomes in real-world healthcare settings.

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