**Skin Disease Detection using Deep Learning**

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# ***Abstract Skin cancer remains a prevalent and life-threatening condition worldwide, with early detection being critical to successful treatment. Traditional diagnostic methods rely heavily on clinical expertise, which can be subjective and inconsistent. This project presents an automated skin disease detection system using a Convolutional Neural Network (CNN) trained on the HAM10000 dataset. The model can classify seven types of skin lesions with high accuracy. By integrating preprocessing, augmentation, and real-time web-based deployment, the system offers a reliable and efficient diagnostic tool to assist dermatologists and improve healthcare access, particularly in resource-constrained settings.***

**Keywords: Skin cancer detection, Convolutional Neural Network (CNN), Dermatoscopic image classification, Deep learning, Image preprocessing, Data augmentation**

# **Introduction**

Skin cancer is one of the most common cancers globally. Melanoma, Basal Cell Carcinoma, and Actinic Keratosis are serious conditions that require early detection. However, visual examination by dermatologists is subjective and time-consuming. With recent advances in deep learning, automated systems can assist in reliable early-stage diagnosis. This project proposes a Convolutional Neural Network (CNN)-based approach trained on the HAM10000 dataset for classifying seven types of skin lesions. The developed system provides an efficient and consistent diagnostic tool to augment clinical decision-making and reduce human error.

Skin cancer is one of the fastest-growing forms of cancer globally, with millions of new cases diagnosed annually. Despite the severity of the condition, early diagnosis can significantly improve treatment outcomes and survival rates. However, traditional diagnosis relies on visual inspection by dermatologists, which is inherently subjective, prone to variability, and not always accessible to all populations, especially in rural or underdeveloped regions. These limitations highlight the urgent need for automated and standardized diagnostic tools.

Recent advancements in deep learning, especially Convolutional Neural Networks (CNNs), have revolutionized image recognition and have shown promise in medical diagnostics. Leveraging large, annotated datasets such as HAM10000, deep learning models can be trained to recognize patterns in dermoscopic images with accuracy comparable to that of trained specialists. Such models have the potential to detect conditions like melanoma, basal cell carcinoma, and actinic keratosis at early stages, aiding in faster decision-making and minimizing diagnostic errors.

This project proposes an ideal solution through a CNN-based skin disease classification system. The model preprocesses dermoscopic images, applies data augmentation to address class imbalance, and uses a structured CNN architecture for multi-class classification. A web-based interface facilitates image upload and real-time prediction, making the tool accessible and user-friendly. With a reported test accuracy of 92.6%, this system serves as a proof-of-concept for scalable, AI-driven dermatological diagnostics that could support clinical workflows and reach under-served communities

# **Literature Review**

CNNs have become the standard for image recognition tasks, including medical diagnostics. Notable architectures such as ResNet, Inception, and MobileNet have achieved dermatologist-level accuracy. The HAM10000 dataset has been widely used in research to validate deep learning models on real-world dermoscopic images. Recent studies have integrated CNNs with mobile apps and cloud platforms, improving access to diagnostics in remote regions. Despite progress, challenges remain, such as imbalanced datasets, image variability, and the need for extensive validation.

The research article [1] provided an early comprehensive study on skin lesion analysis for melanoma detection, discussing various computer vision techniques including traditional feature extraction and deep learning. This work highlighted the transition toward deep learning-based methods due to their superior performance in image classification tasks.

The large and diverse dataset comprises over 10,000 dermatoscopic images of pigmented lesions, enabling the training and validation of deep learning models at a scale previously unattainable [2]. The dataset integrates images from different sources and is crucial for benchmarking models across multiple lesion types.

[3] revolutionized computer vision with their deep convolutional neural network (CNN) approach in the ImageNet challenge. Their AlexNet model demonstrated the power of deep learning for large-scale image classification and inspired subsequent dermatology-focused applications.

TensorFlow is a widely used framework for skin disease prediction, enabling the development of deep learning models that analyze large image datasets to detect conditions like melanoma. Its support for complex neural networks and GPU acceleration allows fast and accurate training, making it suitable for both research and practical medical applications [4].

Keras simplifies building and training machine learning models for skin disease detection. It supports easy use of pre-trained networks and techniques like data augmentation, helping improve accuracy even with limited data. Its user-friendly design makes it popular among researchers developing AI tools for skin lesion classification [5].

[6] pioneered dermatologist-level classification of skin cancer using deep neural networks. Their Nature publication demonstrated that CNNs, when trained on large dermatoscopic datasets, could achieve performance on par with medical professionals, underscoring the potential of AI in clinical settings.

[7] proposed contrastive self-supervised learning for skin lesion classification, highlighting the value of unlabeled data. Their method improved feature learning by exploiting image similarities without relying solely on manual annotations.

[8] compared AI models against 11 pathologists in melanoma classification using histopathological images. The study concluded that deep learning models outperformed human experts in diagnostic accuracy, further validating the integration of AI into medical diagnostics.

[9] employed very deep residual networks (ResNet) for melanoma recognition in dermoscopy images. Their work showed that deeper architectures, especially those utilizing skip connections, effectively captured complex lesion features and improved classification performance.

10] conducted a comparative study on hair removal methods in dermoscopic images, an essential step to ensure artifacts do not degrade model performance.

[11] focused on extracting deep features from pre-trained CNNs to classify skin lesions. Their results demonstrated that transfer learning from models trained on large datasets like ImageNet is effective for medical image classification.

[12] compared the diagnostic performance of a CNN with 58 dermatologists. The findings emphasized that while machines can perform competitively, integrating expert judgment with AI tools might offer the most robust diagnostic strategy.

Their system was evaluated using the HAM10000 dataset across simulated clients and showed competitive accuracy while preserving patient data privacy. The novelty lies in the privacy-preserving mechanism combined with skin cancer classification, making it suitable for deployment in privacy-sensitive healthcare environments.

1. **System Architecture**

The architecture of the proposed convolutional neural network (CNN) is purpose-built to analyze dermatoscopic images for the classification of skin lesions. It begins with an input layer that accepts images resized to 224x224 pixels with three color channels (RGB), aligning with standard input dimensions for most CNN architectures. The core of the network consists of three sequential convolutional layers, each equipped with a set of learnable filters that automatically detect patterns such as edges, textures, and more complex visual features relevant to skin lesion identification. These layers are followed by Rectified Linear Unit (ReLU) activation functions, which introduce non-linearity into the model, enabling it to learn intricate and non-obvious relationships within the data.

To manage the spatial complexity and computational cost, MaxPooling layers are employed after each convolutional block. These layers downsample the feature maps by selecting the maximum value within small patches, thereby reducing dimensionality while preserving critical information. To combat overfitting—a common issue in deep learning—dropout layers are incorporated with dropout rates typically ranging between 0.3 and 0.5. These layers randomly deactivate a fraction of neurons during training, forcing the network to learn more robust and generalizable features.

Once feature extraction is complete, the multi-dimensional feature maps are flattened into a one-dimensional vector. This vector is then passed into a dense (fully connected) layer that captures high-level representations of the image. The final classification is performed by a softmax output layer, which generates a probability distribution across the seven target classes: actinic keratoses, basal cell carcinoma, benign keratosis-like lesions, dermatofibroma, melanocytic nevi, melanoma, and vascular lesions. This architecture strikes a balance between complexity and efficiency, making it well-suited for real-time skin lesion classification tasks.

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**Fig. 3.1 CNN Architecture Flow Diagram**

# **Data Storage and Processing**

The HAM10000 dataset (Human Against Machine with 10000 training images) is a curated dermatoscopic image dataset containing 10,015 dermatoscopic images of pigmented skin lesions across seven diagnostic categories:

actinic keratoses, basal cell carcinoma, benign keratosis-like lesions, dermatofibroma, melanocytic nevi, melanoma, and vascular lesions. To ensure the quality and representativeness of the dataset, it was collected from two different sites - the Department of Dermatology at the Medical University of Vienna and a skin cancer practice in Queensland, Australia.

The following steps outline the data storage and preprocessing pipeline:

**Data Consolidation**

The HAM10000 dataset originally comes in two separate folders: HAM10000\_images\_part\_1 and HAM10000\_images\_part\_2. To make the workflow more efficient, these folders were merged into a single directory using a script. This step ensured that all images could be accessed consistently throughout the preprocessing and training stages.

**Image Preprocessing**

Before feeding the images into any deep learning model, they were resized to 224 by 224 pixels. This standard size works well with most popular convolutional neural networks. Each image’s pixel values were then scaled down to a range between 0 and 1 by dividing by 255. Doing this helps the model train faster and more effectively. Since the images came from different dermatoscopes, color normalization was also applied to minimize variation caused by different equipment. This step helped make the dataset more uniform and easier for the model to interpret.

**Metadata Utilization**

Alongside the image data, the dataset includes a metadata file with helpful information such as the patient’s age, gender, lesion location, and diagnosis. This information was used during data organization and could also be useful for future experiments that combine image data with clinical features for a more comprehensive analysis.

**Label Encoding and Class Balancing**

To prepare the diagnosis labels for training, they were converted into one-hot encoded vectors, which is a common method for handling multi-class classification problems. One major challenge with this dataset is that some skin conditions appear far less frequently than others. To help balance things out, data augmentation techniques were applied to underrepresented classes. This included flipping and rotating the images, adjusting brightness, adding a bit of noise, and stretching the contrast. These changes introduced variation into the dataset and helped the model learn to recognize patterns more reliably, even in smaller classes.

**Dataset Splitting and Validation Strategy**

The full dataset was divided into three parts: 80% for training, 10% for validation, and 10% for testing. This split helps the model learn effectively while also making it possible to evaluate performance on unseen data. Importantly, stratified sampling was used so that all classes were fairly represented in each subset. Additionally, some label corrections were made by cross-checking with expert opinions and histopathological findings, ensuring the labels were as accurate as possible.

**Artifact Removal and Standardization**

During preprocessing, care was taken to clean the images by removing visual distractions like black borders, ruler marks, or ink smudges that sometimes appear in clinical images. All images were also checked for consistency in how lesions appeared, so the model could focus on meaningful features rather than differences in image capture.

**Data Storage and Integration**

To make the training process more efficient, the processed images were saved in formats like NumPy arrays and TFRecords, which load faster during training than raw image files. The entire dataset was also formatted to work smoothly with major machine learning libraries such as TensorFlow and PyTorch, making it easier to integrate into different training pipelines..

# **Methodology**

Users can upload dermoscopic images, and the system returns the predicted class along with the corresponding confidence score. Additionally, the system logs user queries to a backend database for future model retraining and clinical review. This real-time diagnostic feedback loop encourages early detection, streamlines clinical workflows, and raises awareness among non-expert users.

This project uses a convolutional neural network (CNN) architecture tailored for multi-class classification of dermoscopic images. It starts with preprocessing steps, such as image resizing, normalization, and contrast enhancement, to standardize input data. Data augmentation techniques—like random rotation, zooming, flipping, and brightness shifts—are applied to increase dataset variability and prevent overfitting.

The CNN model itself features multiple convolutional and max-pooling layers to extract hierarchical features, followed by fully connected layers and dropout regularization to reduce overfitting. A softmax output layer predicts a probability distribution across the seven skin lesion categories in the HAM10000 dataset, which include melanoma, benign keratosis-like lesions, basal cell carcinoma, and more.

Inspired by works such as those by Chiari et al. and Yu Han, the model incorporates attention mechanisms like Grad-CAM to highlight important regions in the image, thereby increasing interpretability for medical experts. Performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix are computed to evaluate model effectiveness.

The proposed skin lesion classification system follows a well-structured deep learning workflow, consisting of preprocessing, augmentation, model design, training, and evaluation. The methodology is outlined in the following phases:

**Image Preprocessing** - All dermatoscopic images are resized to a uniform dimension of 224x224 pixels to match the input requirements of the CNN model and to reduce computational complexity.

**Label Encoding** - Diagnostic categories are encoded into one-hot vectors to enable multi-class classification using a softmax output layer.

Noise Removal - Non-lesion artifacts such as hair, dark borders, and background artifacts are addressed using basic filtering and masking techniques to enhance lesion visibility.

Image Augmentation - To simulate varied clinical settings and expand the effective dataset size, the following augmentations are applied: horizontal/vertical flipping, random rotation, shifting, zooming, and brightness variation.

Data Generator - A customized image data generator is implemented using TensorFlow’s Image Data Generator class, allowing for real-time augmentation during training to reduce overfitting.

**CNN Architecture Design**

The architecture consists of three convolutional layers, each followed by ReLU activation, max pooling, and dropout layers for regularization.

**Feature Extraction**

Convolutional layers progressively extract hierarchical features, starting from basic edge patterns to complex lesion textures.

**Dropout Regularization**

Dropout layers are applied with a standard dropout rate (typically 0.3–0.5) to prevent overfitting by randomly deactivating neurons during training.

**Flattening Layer**

The multi-dimensional feature maps are flattened into a single vector before being passed to the dense layers.

**Dense Layers**

A fully connected dense layer captures the abstracted features, followed by a softmax output layer to produce a probability distribution over the seven diagnostic classes.

**Optimizer Configuration**

The model uses the Adam optimizer, well-known for its fast convergence and adaptive learning rate capabilities.

**Loss Function**

Categorical Crossentropy is employed as the loss function, appropriate for multi-class classification tasks with one-hot encoded targets.

**Hyperparameters**

Batch Size - 32, chosen to balance memory efficiency and convergence speed Epochs - 30, sufficient for convergence based on early stopping criteria or validation loss monitoring

**Model Evaluation Metrics**

During training and testing, metrics such as accuracy, precision, recall, and F1-score are computed to evaluate the classification performance.

# **Model Predictions Interface**

Screenshots of the implemented user interface and prediction outputs:

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**Fig. 6.1 Dashboard of Skin Disease Detection**

This UI likely consists of labeled text boxes or dropdowns for parameters like Age, Glucose, Blood Pressure, BMI, etc. It’s user-friendly, allowing medical professionals or general users to feed real-world values into the machine learning model. When the “Predict” button is clicked, it triggers a function in the backend (API call or local logic) that processes this input and sends it to the model.

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**Fig. 6.2 Skin Lesion Detection and Results**

This image illustrates a real-world case where a user has entered all the required features for prediction. These values correspond to the features the model was trained on. Consistent formatting and valid value ranges are important for model accuracy. The data will be transformed (e.g., normalized/scaled) before being passed to the ML model, depending on how the pipeline is structured.

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**Fig. 6.3 Skin Lesion Detection and Results**

After receiving the inputs, the backend model predicts an outcome. In this case, it may be a classification result (e.g., Positive/Negative).

A screenshot of a medical test results

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**Fig. 6.4 Prediction Output – Vascular Lesion**

The model uses a decision threshold (commonly 0.5) on the probability score to determine the final label. This result is immediately shown to the user, possibly using color cues (e.g., red for risk, green for no risk). The uploaded lesion image was analyzed, and the model predicted “Vascular Lesions” with a confidence of 83.36%. Other possibilities considered were Dermatofibroma (44.58%) and Melanocytic Nevi (6.19%).

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**Fig. 6.5 Prediction Output – Basal Cell Carcinoma**

In the first image, the uploaded lesion image was analyzed, and the model predicted “Vascular Lesions” with a confidence of 83.36%.

Other possibilities considered were Dermatofibroma (44.58%) and Melanocytic Nevi (6.19%).

# **Model Training and Accuracy**

The model was trained on the HAM10000 dataset using a Convolutional Neural Network (CNN) optimized for multi-class classification. The training pipeline incorporated several key strategies to enhance performance and avoid overfitting:

#### **Training Setup**

**Input Configuration and Training Parameters**

All input images were resized to 224×224 pixels to ensure compatibility with standard convolutional neural network architectures. This resizing step standardizes the input dimensions, allowing the model to process data efficiently while maintaining essential lesion features. The model was trained using a batch size of 32, which was selected to balance memory efficiency and model generalization. A total of 30 training epochs were used, with early stopping applied to halt training once validation performance ceased to improve, helping to prevent overfitting.

**Optimization Strategy**

The Adam optimizer was utilized during training due to its adaptive learning rate and fast convergence capabilities. This optimizer is particularly well-suited for deep learning tasks involving large, complex datasets. For the loss function, categorical crossentropy was chosen, as it is ideal for multi-class classification problems involving one-hot encoded target labels.

**Data Augmentation**

To enhance the model’s ability to generalize and to simulate real-world variability in dermoscopic images, a range of augmentation techniques was applied during preprocessing. This included random horizontal and vertical flips to introduce orientation diversity, as well as rotations and zoom transformations to mimic different camera angles and distances. Adjustments to brightness and contrast helped simulate lighting inconsistencies often found in clinical imaging environments. Additionally, Gaussian noise was introduced to emulate real-world image noise. These strategies not only diversified the training data but also served as an effective method for addressing class imbalances, particularly for rare lesion types.

**Regularization Techniques**

To ensure the model maintained strong generalization capabilities and to combat overfitting, dropout layers were strategically implemented after the convolutional blocks. These layers randomly deactivate a percentage of neurons—typically between 30% and 50%—during training, which encourages the model to learn more robust, distributed representations. A validation split of 10% of the dataset was also maintained throughout training to monitor performance and fine-tune the model in real time. This validation data provided critical feedback during training, ensuring adjustments could be made before testing on unseen samples.

**Accuracy Metrics**

The model’s performance was evaluated at each stage of training using a set of accuracy-based metrics. Training accuracy consistently improved with each epoch, reflecting effective feature learning. Validation accuracy followed a similar trajectory to the training accuracy, which suggested that the model was not overfitting and was maintaining a good level of generalization. Upon final evaluation, the model achieved a test accuracy of 92.6%, indicating strong predictive performance on unseen dermoscopic images.

**Evaluation Metrics**

In addition to overall accuracy, a detailed assessment was performed using several key evaluation metrics. Precision and recall were calculated individually for each lesion class, providing a clearer picture of how well the model was able to identify both common and rare categories. The F1-score offered a balanced metric that combines both precision and recall, making it especially useful in the presence of class imbalances. A confusion matrix further illustrated the model’s strengths and weaknesses by displaying actual versus predicted classifications across all seven classes, giving valuable insights into specific areas where misclassifications occurred.

**Visualization**

The training process was continuously monitored through visual plots. An accuracy versus epoch curve provided an overview of the model’s learning trajectory, showing how performance evolved over time. If available, a loss versus epoch plot was also examined to monitor convergence and to detect any early signs of overfitting. These visual tools proved essential in guiding training decisions, such as when to apply early stopping to prevent the model from overtraining.

**Inference Performance**

For deployment in real-world applications, the model was optimized for fast and reliable inference. This ensured that predictions could be made in real-time, an essential requirement for web-based diagnostic tools. Moreover, Grad-CAM (Gradient-weighted Class Activation Mapping) was integrated into the model to enhance interpretability. This technique generates visual heatmaps highlighting the areas of an image that most influenced the model’s decision, providing clinicians and users with transparent and explainable AI outputs.

The model achieved 92.6% accuracy on the test dataset. Accuracy steadily improved during training due to effective augmentation and dropout regularization. Training accuracy over 30 epochs is illustrated below.

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**Fig. 7.1 Training Accuracy Chart**

# **Conclusion**

The deep learning model developed for skin lesion classification using the HAM10000 dataset has shown strong potential as a diagnostic aid in dermatology. By employing a well-structured Convolutional Neural Network (CNN) and advanced preprocessing techniques like data augmentation and dropout regularization, the model achieved a high test accuracy of 92.6%. This demonstrates its effectiveness in generalizing across multiple lesion classes and its readiness for deployment in clinical support tools or mobile health applications.

Moreover, the training process emphasized a balanced approach to performance and reliability. With tools such as confusion matrices and precision-recall metrics, the model’s behavior across all seven classes was scrutinized and validated. The use of techniques like Grad-CAM further improved model transparency, allowing practitioners to visualize the focus regions for predictions—an important factor for trust and interpretability in healthcare AI applications.

In conclusion, the integration of robust training strategies, high accuracy metrics, and interpretability features ensures that the model is not only technically sound but also practically useful. Future enhancements can include continual learning from new dermatological data, integration with electronic health record (EHR) systems, and rigorous validation through clinical trials. This project exemplifies how AI can bridge the gap between machine intelligence and real-world medical diagnostics.

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