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Research Article

Deep Learning for Disease Classification in Teledermatology System Using Dermoscopic Skin Images

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Abstract:

In recent years, the popularity of Deep Learning has surged. Among the most well-known architectures in Deep Learning are Neural Networks, including Convolutional, Recurrent, and Generative Adversarial Networks. Convolutional Neural Networks (CNNs) have become an important architecture for image classification tasks due to their superior accuracy and performance. Skin cancer, the most common form of human cancer, has an extremely high cure rate when detected and treated at an earlier stage. However, automated categorization of skin lesions is challenging due to the fine-grained heterogeneity in their appearance. This study proposed a CancerVisionNet (CNNs) model to predict and categorize seven distinct types of skin lesions. The "Human Against Machine with 10000 training images" (HAM10000) dataset, which contains dermoscopic images, is used in this research to evaluate the proposed method for diagnosing and organizing skin disorders. ReLU as an activation function is employed to handle non-linearity in hidden layers. Our proposed method achieved a higher accuracy (79.6%) than other state-of-the-art methods such as with accuracies of 75.03% and 74.3%. This paper shows the effectiveness of the proposed method in disease classification using dermoscopic skin images in the context of teledermatology.

Keywords: Convolutional Neural Networks; Deep Learning; Dermoscopic Image; Skin Diseases; VGG.

1. Introduction

Convolutional Neural Networks (CNNs) take cues from the mammalian visual brain as a form of deep learning architecture. They have been used in image categorization, natural language processing, automatic caption generation, and other applications. CNNs are gaining recognition in various fields, including medical diagnostics [1]. CNNs facilitate fast and accurate image classification and have potential in medical applications, particularly for detecting diseases from imaging data [2]. Cancer is a heterogeneous group of diseases characterized by the unchecked growth and spread of malignant tumors from their original sites [3]. Skin cancer has the highest incidence rate and is the most dangerous of all cancer types. Melanoma and non-melanoma skin cancers make up the vast majority of all cancer cases.

With massive datasets, the CNN has been shown to be both practical and efficient. The cell mask has been previously predicted in [4] using a

Function Pyramid Network (FPN) and a combination of neural nets and VGG-style. Goceri et al. [5] proposed employing fully convolutional networks (FCNs) with many stages for skin lesion segmentation. They claimed that they have achieved better detection in their work by merging the results of a parallel integration technique. Skin lesion segmentation and classification have been approached from many angles [6]. According to Lembhe et al. [7], the suggested strategy employs computer vision-based deep learning techniques. Algorithms trained with supervised and deep learning may provide better skin cancer diagnoses.

The following datasets were used in the systematic review by Grignaffini et al. [8]: MedNode, ISIC2017, HAM10000, ISIC2016, PH2, DermIS, DermQuest, ISIC archive, IDS, ISIC 2019, ISIC2020, ISIC2018, 7-point checklist, and DermNZ. The authors aimed to identify and categorize skin cancer using machine learning techniques.

Dermatologists may find dermoscopy, a non-invasive imaging technique, useful in clinical assessments for the more reliable detection of melanoma [9]. The death rate from melanoma is higher than that of any other skin cancer. If dermoscopy images can distinguish between malignant and benign skin lesions instead of clinical imaging, it would be a huge step forward in the fight against melanoma [10]. Meanwhile, CNNs and other deep-learning approaches have recently shown remarkable effectiveness in various image identification applications [11, 12]. CNN's most notable feature is its ability to help derive comprehensive visual representations from the training data [13]. According to a study [14], the (CNN) models that were previously trained on a massive ImageNet dataset showed promising results on various image identification tasks without the need for retraining. A few studies have so far attempted to classify dermoscopy images using transferred CNN features [15]. Melanoma classification using deep features extracted directly from original images may also perform poorly for skin images with inter-class homogeneity and intra-class variability.

The healthcare costs and cancer mortality rates associated with malignant lesion types are pretty high. Because malignant melanocyte cells may divide uncontrolled, infiltrate neighboring organs, and metastasize widely, early diagnosis is essential to reducing death rates [16]. Dermoscopy, also known as Epiluminicence Microscopy (ELM), is a standard tool doctors use to identify skin lesions as either cancerous or noncancerous.

The DNA of skin cells may be damaged by the sun's ultraviolet (UV) rays, making them more vulnerable to cancer. DNA damage may lead to gene alterations, which in turn can trigger the unchecked proliferation of skin cells and the development of tumors. Sunlight isn't the only thing that may cause skin cancer; genetic abnormalities play a role, too [17].

Skin lesions might result from several factors, including allergic reactions, cancer cells, etc. However, malignant tumors on the skin are very dangerous. Some forms of skin cancer may be lethal if left untreated. With an unacceptably high mortality rate of 8%, melanoma is the skin cancer that kills the most people. Dermatologists use diagnostic procedures to find skin cancer, the most common human malignancy, including clinical screenings, dermoscopy, biopsies, and histological tests [18].

Recent work applies digital image processing to dermoscopy for classifying benign and malignant lesions [19]. The accuracy of deep neural networks surpassed that of dermatologists. There are a few different systems that dermatologists use to categorize lesions. The skin lesion is diagnosed as melanoma if two of the following three criteria are satisfied throughout the diagnostic process:

- Asymmetries: variations in shape and color along one or two orthogonal axes
- Unusual structure: pigment network with crooked holes and heavy outlines
- Blue-white structures: a mix of blue-white veil and regression structures, or any other blue and white color scheme.

First, a dermoscopic expert uses a magnifying lens called dermoscopy to examine the lesion under a microscope, followed by a biopsy to confirm the diagnosis. However, these traditional approaches

require more effort, money, and time, and the reliability of diagnoses and prognoses depends on experts' subjective knowledge and experience [20].

"Teledermatology" describes the field that uses telecommunications technology to provide dermatological diagnosis, treatment, and care to patients [21]. The first mode, "real-time," enables immediate communication between patients and medical professionals; the second, "store-and-forward," provides for the storage of patient data for subsequent access by medical professionals [22]. With the help of automated classification systems like a Convolutional Neural Network, teledermatology can offer fast and accurate diagnoses, complementing traditional methods like visual first clinical screening, dermoscopy imaging analysis, biopsies, and histological exams [23]. Using 10,015 color photos, this study suggests a convolutional neural network (CNN) model for classifying seven skin lesions. Fully Connected Layers, Convolution Layers, and Pooling Layers are all part of the model [24].

1.1 Research Gap

Several obstacles in teledermatology skin categorization utilizing dermoscopy skin images necessitate more research. A major constraint in the literature is the small number of publicly accessible skin cancer datasets, even though deep learning methods (particularly CNNs) have shown promise in image classification tasks. When faced with limited datasets, deep learning models, especially those with many parameters, are prone to overfitting due to inadequate training data. Not to mention that a lot of the CNN models received their characteristics straight from the source images, which means they could have missed some crucial lesion-specific details.

Our proposed model, CancerVisionNet, can identify and categorize seven distinct skin lesions using convolutional neural networks. Our work primarily focuses on the "Human Against Machine with 10000 training images" (HAM10000) dataset, which is publicly available via the ISIC Archive and used in a research work [25]. It is a diversified collection of dermoscopy images donated by the International Skin Image Collaboration (ISIC). This dataset depends on the development of a reliable method for the classification and diagnosis of skin disorders. Our study's results have far-reaching implications in the medical and technology fields, highlighting the practical advantages of deep learning for dermatological diagnosis. The proposed research question is given as follows:

RQ1: How can we develop a customized CNN-based framework (CancerVisionNet) to enhance the accuracy of skin lesion classification in teledermatology and decision making in skin cancer diagnosis?

In view of the proposed research question and research gap, this study has the following contributions.

1.2 Research Contribution

a) This study introduces a novel automated system utilizing CancerVisionNet, a customized CNN, to predict and classify seven distinct skin lesions accurately.
b) This paper compares CancerVisionNet's performance to other popular pre-trained CNN architectures and investigates the efficacy of deep visual features derived from CancerVisionNet. In this comprehensive study, the HAM10000 dataset is used to evaluate eight distinct CNN models.
c) This study tests the suggested method on the HAM10000 dataset to prove its effectiveness, and it passes with flying colors. It goes a step further by contrasting the model's output with cutting-edge techniques, offering a yardstick to measure its precision.
d) The research presents results from informative ablation experiments that clarify important aspects like normalization methods, features at different CNN layers, preprocessing approaches, and train-test split ratios. The results help shed light on how well and how resilient the suggested technique is in various environments.

e) Fused deep features concatenated from multiple layers of the CNN architecture are an innovative part of this study, which aims to explore their influence. This article focuses on finding the best fusion techniques for better skin categorization and delves into features at the data, intermediate, and decision levels.

The remainder of this paper is structured as follows:

Section 2 presents the related work. Section 3 proposes a method for disease classification based on dermoscopic skin images. Section 4 is focused on the experimental results obtained from applying the proposed method to a dataset of dermoscopic skin images. Section 5 gives a discussion on results and findings in this study, and Section 6 concludes the main points and research implications.

2. Related Work

Hekler et al. [27] used the HAM10000 dataset for skin lesions classification by application of CNN models. The authors used normal convolutional layers and the K-Fold validation technique, without pre-processing or combining many feature batches. Although the CNN model obtained the best accuracy of 75.03%, its architecture was otherwise shallow, and they did not experiment with normalization layers or dropout regularization to improve model generalization. This demonstrates the poor performance of baseline CNNs for imbalanced dermoscopic data. In another research work, Mporas et al. [28] conducted pre-processing steps for a pigmented skin lesion classification (potential hair removal and segmentation) and fashion properties for practical class-formation, and colors feature extracted from color spaces (RGB, HSV, YIQ). Unlike other approaches using deep CNNs, the paper applied machine learning classifiers, and the best performance was obtained by using AdaBoost combined with the Random Forest model. The models were evaluated using the HAM10000 dataset. This research study provided an accuracy of 74.3%, showing the promise of handcrafted color features. However, they showed limitations when compared to deep learning architectures.

Bisla et al. [29] proposed to use CNNs to detect melanoma and largely focused on data pre-processing and augmentation techniques. The limitations in the dataset, including class imbalance and occlusion, were tackled by introducing purification techniques and GANs to synthesize rare lesion types. The CNN model demonstrated 71.7% accuracy, which was validated using the ISIC 2017 and ISIC 2018 datasets. Both methods used in this study showed strength in dealing with datasets. However, the use of synthetic data results in serious concerns about extensibility when dealing with real-world clinical cases. Therefore, the proposed CancerVisionNet (CVN) method is evaluated only using real-world datasets.

Aswath and Cholan [30] developed a hybrid approach based on image processing and machine learning to classify multiple skin diseases automatically. Feature extraction used GLCM, HOG, LBP, and color histograms as classical descriptors and an extended version of Xception [8]. Using common machine learning models such as Random Forest, SVM, and CatBoost for classification, the extended Xception proved to be a better model compared to other models. However, overall accuracy figures were not given in the study for comparing directly with independent CNN-based methods, but showed the potential of both handmade and deep hybrid features.

In contrast, our proposed CVN method is a deeper CNN combined with convolutional layers, batch normalization, and dropout regularization, with fully connected layers to learn hierarchically lesion features whilst preventing overfitting. The CVN achieves an improved test accuracy of 79.6% vs.73.4% in [26], 77.1% in [29] on the HAM10000 dataset, unlike previous work [28,30], which used only handcrafted features, or shallow CNNs [26,28]. Hence, this makes CVN a better solution, achieving a favorable balance between architectural complexity vs decorative fit and dominating other competitive methods in accuracy and stability.

3. Proposed Method

The proposed deep learning model, the CancerVisionNet system for skin disease classification, is

designed to work on the MNIST HAM10000 dataset. The first step involves splitting the datasets into training, validation, and testing data, which is then preprocessed for further analysis. The model is evaluated and optimized during the training process to achieve the best possible results. The CNN model is the core of this proposed model system and is used to classify the skin disease images in the testing process. The model evaluation is then repeated to verify the model's accuracy, and the testing process provides the final classification results. Overall, this model system structure ensures that the dataset is split, preprocessed, and trained efficiently to achieve accurate results in skin disease categorization using deep learning. Figure 1 shows the block diagram of the suggested model.

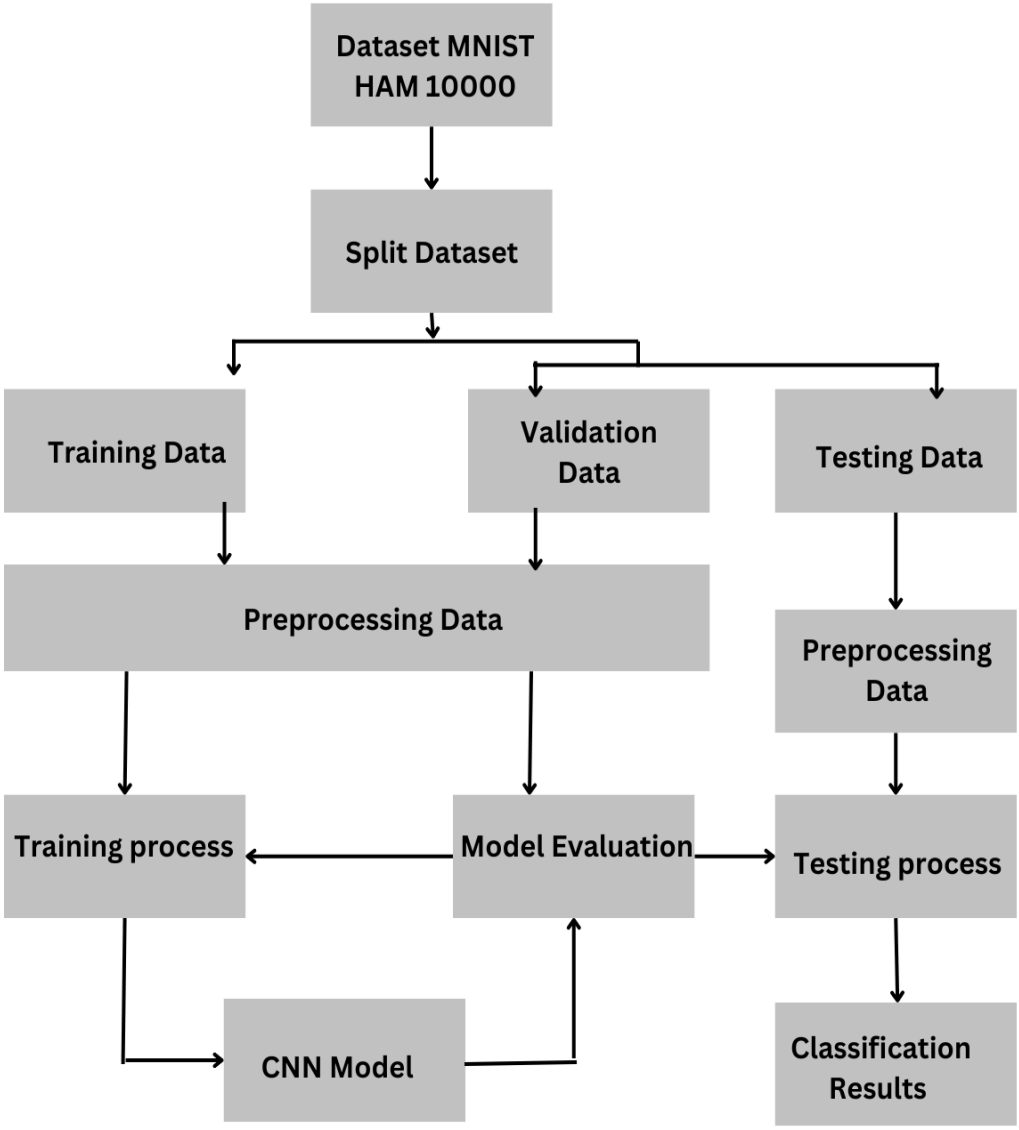

Figure 1: Proposed scheme of research

CNNs are trained using the preprocessed training data and used as the system's deep learning model. After training the model on the training data, its accuracy is further enhanced by evaluating it using the preprocessed validation data. The CNN model is used to categorize the preprocessed testing data, and the final results are achieved by evaluating the model using this data. The resulting classification results are examined to assess how well the model performs and how accurate it is in diagnosing various skin disorders from dermoscopy images.

3.1 Dataset

The MNIST HAM1000 dataset is used in this study, which is a publicly accessible, massive collection of multisource dermoscopic images of pigmented lesions [28]. This information may be accessed from Kaggle. We narrow our focus to seven kinds of disorders affecting the skin: Dermatofibroma (df), basal cell carcinoma (bcc), melanocytic nevi (nv), actinic keratoses (akiec), vascular lesions (vasc), Benign keratosis-like lesions (bkl), and melanoma (mel) are all types of skin cancer (see Figure 2).

HAM10000 (Human Against Machine with 10000 training images) consists of 10,015 dermoscopic images of seven common categories of pigmented skin lesions: melanoma, melanocytic nevus, basal cell carcinoma, actinic keratosis, benign keratosis, dermatofibroma, and vascular lesion. These images are mainly 450 × 600 pixels in size and were collected from various clinical sources with different acquisition devices. Due to its larger size, clinical relevance, and wide adoption as a benchmark dataset for automated skin lesion classification, we used this dataset in our study. A sample of images has been given in the following Figure 2.

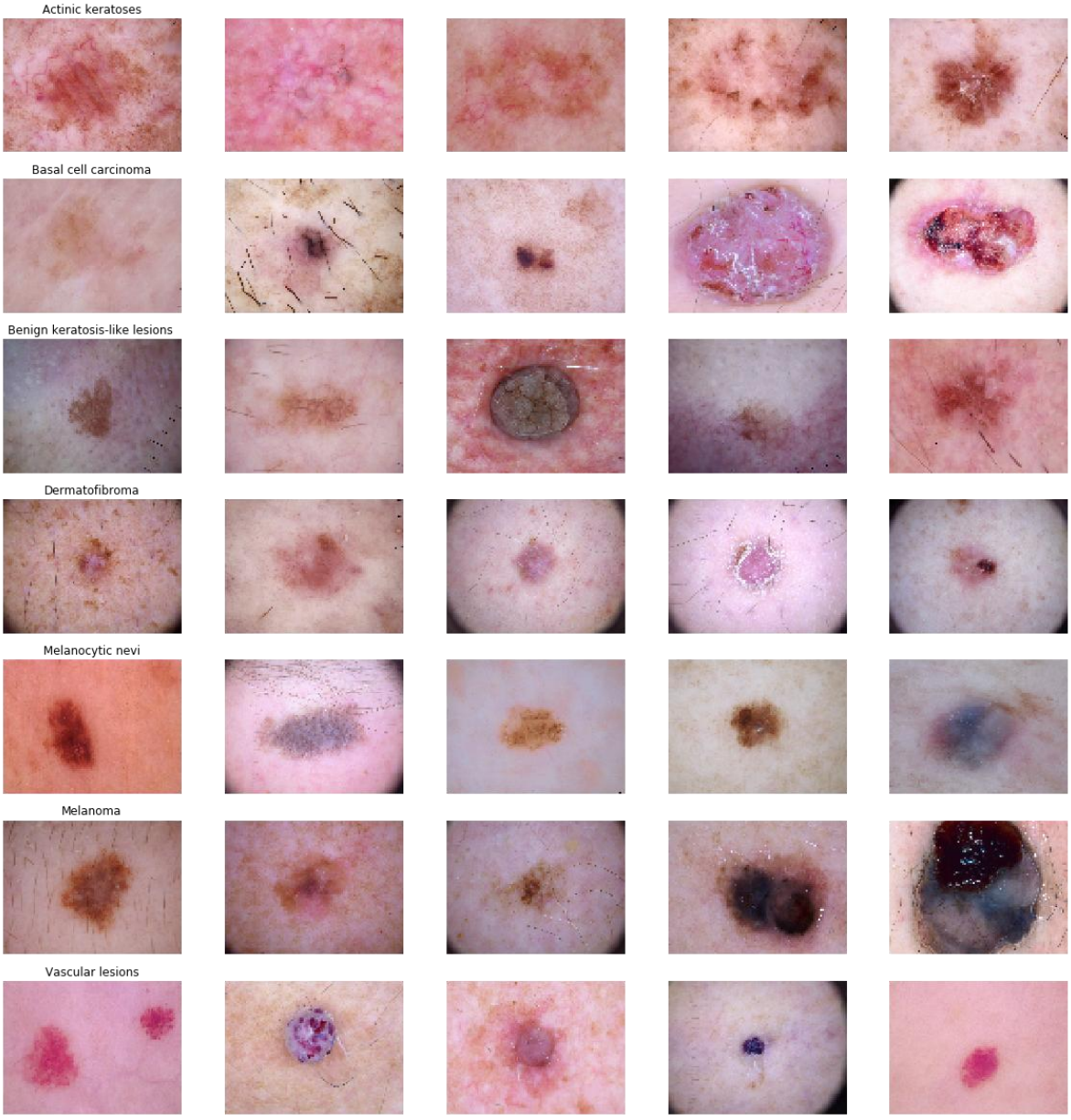

Figure 2: A sample of the MNIST HAM1000 dataset

The structure of the HAM10000 dataset, which contains images classified into exactly seven clinically relevant lesion types, determined the selection of seven skin disorder categories. We use HAM1000 as a benchmark dataset and therefore, restrict our classification to these categories and make sure that we achieve consistent results with the existing research studies.

3.2 CancerVisionNet (CVN)

A CNN's design differs from a standard Multi-Layer Perceptron (MLP) as it offers evidence of shift and distortion invariance. A CNN comprises multiple layers, making it a trainable multistage architecture [26]. Feature maps are inputs and outputs at every level. Each color channel has a two-dimensional array of pixel values for colored input images. A convolution, nonlinearity, and pooling layer make up each step. After one or two stages, a fully connected layer is formed by concatenating convolution and pooling layers.

- A convolutional network's (CNN) foundational layer consists of learnable filters that traverse the entire input space. These filters cover small sections of the image at a time and output a kernel for each area; this is calculated by adding together the values of the filter and the related pixels. We obtain a single feature map by moving the kernel across the entire image space. The convolution layer generates a set of feature maps when multiple kernels are used, and the weight vector for the feature map is shared, reducing the model's complexity.
- Activation functions are employed in the neuron layer to achieve the necessary non-linearity in multi-stage neural networks. These functions include sigmoid, ReLU, and other activation functions. This layer of neurons enhances the accuracy and efficiency of the neural network by introducing non-linearity to the system, allowing for more complex data patterns to be recognized and processed.
- The next layer in the neural network architecture is the pooling layer. It takes the output of the convolution layer, a collection of small boxes, and calculates the maximum or average value in each box. This process helps to prevent overfitting by reducing the complexity of the model while retaining essential features.
- At the end of the model, one or two fully connected layers are added, linking all neurons from the preceding layer to those in the last layer.

In the following Table 1, we provide the layers of the CancerVisionNet architecture.

Table 1: Layers of CancerVisionNet architecture

Layer (Type)	Output Shape	Param-eters	Operation / Description
conv2d (Conv2D)	(None, 75, 100, 64)	1792	Convolutional layer with 64 filters, kernel size 3x3, ReLU activation, padding same
batch_normalization (BatchNormalization)	(None, 75, 100, 64)	256	Normalize the activations of the previous layer per batch
conv2d_1 (Conv2D)	(None, 75, 100, 64)	36928	Convolutional layer with 64 filters, kernel size 3x3, ReLU activation, padding same
batch_normalization_1 (BatchNormalization)	(None, 75, 100, 64)	256	Normalize the activations of the previous layer per batch
max_pooling2d (MaxPooling2D)	(None, 37, 50, 64)	0	Max pooling layer with pool size 2x2

dropout (Dropout)	(None, 37, 50, 64)	0	Randomly drop 25% of the units in the previous layer
conv2d_2 (Conv2D)	(None, 37, 50, 128)	73856	Convolutional layer with 128 filters, kernel size 3x3, ReLU activation, padding same
batch_normalization_2 (BatchNormalization)	(None, 37, 50, 128)	512	Normalize the activations of the previous layer per batch
conv2d_3 (Conv2D)	(None, 37, 50, 128)	147584	Convolutional layer with 128 filters, kernel size 3x3, ReLU activation, padding same
batch_normalization_3 (BatchNormalization)	(None, 37, 50, 128)	512	Normalize the activations of the previous layer per batch
max_pooling2d_1 (MaxPooling2D)	(None, 18, 25, 128)	0	Max pooling layer with pool size 2x2
dropout_1 (Dropout)	(None, 18, 25, 128)	0	Randomly drop 40% of the units in the previous layer
conv2d_4 (Conv2D)	(None, 18, 25, 256)	295168	Convolutional layer with 256 filters, kernel size 3x3, ReLU activation, padding same
batch_normalization_4 (BatchNormalization)	(None, 18, 25, 256)	1024	Normalize the activations of the previous layer per batch
conv2d_5 (Conv2D)	(None, 18, 25, 256)	590080	Convolutional layer with 256 filters, kernel size 3x3, ReLU activation, padding same
batch_normalization_5 (BatchNormalization)	(None, 18, 25, 256)	1024	Normalize the activations of the previous

3.3 Pre-processing Steps

During pre-processing, a few steps were needed to prepare the dataset for the model's training. The first step was that we added more columns for image path, lesion type, and indices, where the categorical column was used to make sure that consistent references while training. The next step was data cleaning, to check for missing values and for field type validation. Then, all the images were held and resized from 450×600×3 to 100×75 pixels in order to minimize computational complexity and maintain essential visual features. The normalization of pixel values was then performed in order to facilitate a fast convergence, improving the model stability. All these preprocessing steps made sure that the input data is standardized, balanced, and suitable for deep learning classification.

It was not an arbitrary choice of design in this study. The progression of filters such as 64–128–256 has been widely used following the CNN patterns. Features complexity increases with the depth increase, which allows layers to learn the low-level edges and layers to learn deeply for capturing the rich lesion patterns. We used a 25% dropout in deeper layers to block the overfitting and a 40% dropout in deeper layers due to the high count of their parameters and higher risk of overfitting. In piloting experiments, a configuration has been validated that provided us the significant, stable training and generalization performance.

4. Experiments and Results

4.1 Proposed Model Training

The model is trained using the MNIST-HAM10000 dataset. About 10000 images have been classified,

representing 7 distinct skin lesions in this collection. Table 2 displays the seven distinct cutaneous lesion types and where they tend to occur.

Table 2: Every skin lesion and its corresponding label

Skin Lesions	Label
Actinic keratosis	0
Basal cell carcinoma	1
Benign keratosis-like lesions	2
Dermatofibroma	3
Malignant Melanoma	4
Melanocytic nevi	5
Vascular lesions	6

4.2 Training and Implementation of the Model

The dataset was divided into 80% for training and 20% for testing. From the training set, 15% of the images were further separated and used as a validation set during model training, resulting in an effective split of 68% training, 12% validation, and 20% testing. All images were resized from their original resolution of 450×600×3 to 224×224×3 for computational efficiency. The VGGNet CNN architecture was then employed, utilizing selected layers.

We chose categorical cross-entropy loss because it works well for multi-class classification. We used the Adam optimizer (learning rate = 0.001) during training because it adjusts momentum, which has shown good results in CNN image classification. To keep training stable and avoid overfitting, the learning rate was halved every 5 epochs. This schedule was tested in early experiments and aligns with common practices. The model was trained for 50 epochs.

Table 3 shows that accuracy and loss varied a bit across epochs but stayed in a stable range. This suggests the model reached a balance without major overfitting or underfitting problems. The use of categorical cross-entropy with Adam and the learning rate reduction schedule helped keep information stable over the 50 epochs.

The dataset was split into 80% for training and 20% for testing. Fifteen percent of the images from the training set were separated and defined as a validation set used during training of the model, so that the splits effectively became 68% for training, 12% for validation, and 20% for testing. For computational efficiency, all images were resized to 224×224×3 pixels from their true resolution of 450×600×3 pixels. Afterwards, the VGGNet CNN architecture was used with the chosen layers.

Next, we used categorical cross-entropy loss for the objective function because it works perfectly with multi-class classification problems. We used the Adam optimizer with a learning rate = 0.001 during the training of the model. The Adam combines the advantages of two popular optimizers (AdaGrad and RMSProp) to adapt the learning rate based on the training performance and works well in CNN-based image classification tasks. The learning rate was also halved every 5 epochs to provide additional stabilization during training and to reduce overfitting. The schedule was tuned empirically based on preliminary experiments and aligned with the previous literature on deep learning approaches. The model was trained on 50 epochs.

The accuracy and loss values fluctuate a little from epoch to epoch in a range of values, which means that the model converged very well without severe overfitting or underfitting, as shown in Table 3.

Categorical cross-entropy, Adam, and a learning rate reduction schedule provided us stability that lasted through 50 epochs. Figure 3 shows us the confusion matrix results.

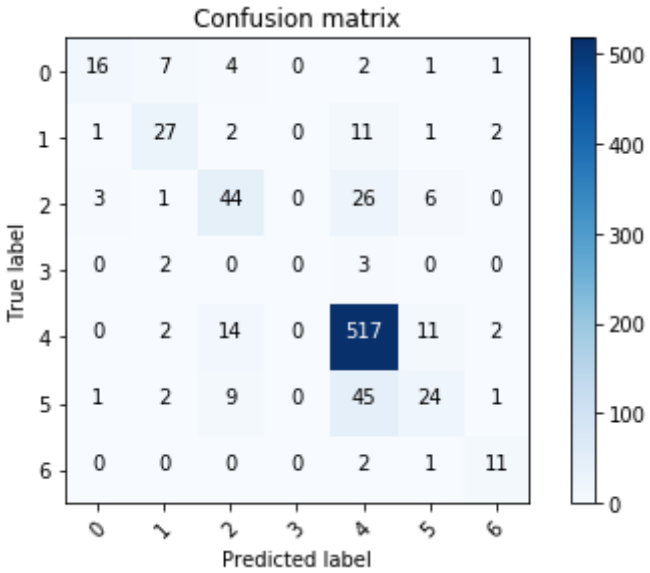

Figure 3: Confusion matrix training process

After training the model for 50 epochs, a test accuracy of 79% was achieved. Over time, both training and testing data accuracy showed improvement. Following the first 30 epochs, training and test loss values steadily decreased at a constant exponential rate. In Figure 4, a scatter plot is presented, displaying the training and testing accuracy and loss values. After the 30-epoch mark, saturation was observed for the times thereafter.

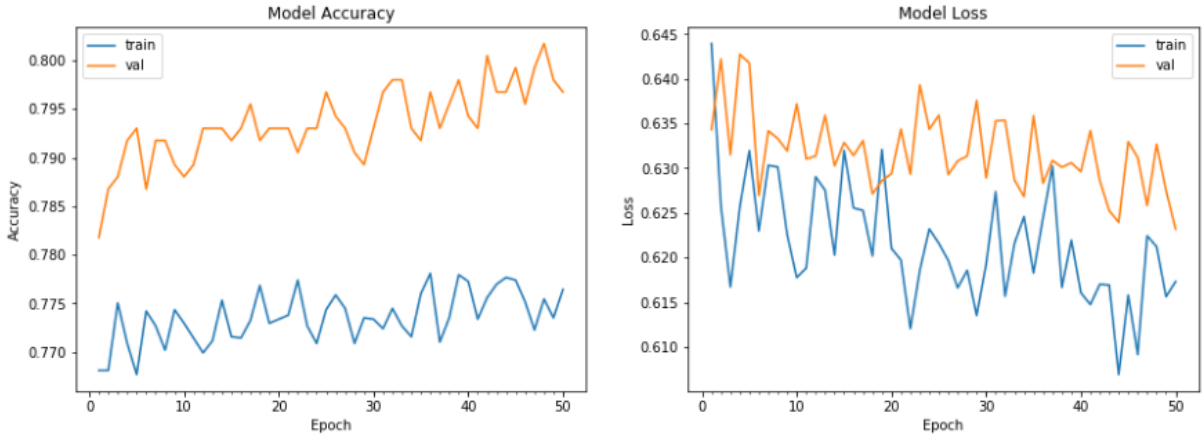

Figure 4: Plots of loss and accuracy

In this research, a deep learning model was trained for 50 epochs. Accuracy and loss were recorded after every 5 epochs. The model's accuracy starts at 0.7930 with a loss of 0.6320 for the first 5 epochs, and the accuracy slightly decreases to 0.7880 with a loss of 0.6372 for the next 5 epochs. However, the model's accuracy improves again at 0.7918 with a loss of 0.6329 for the 15th epoch. The accuracy continues fluctuating for the following few epochs but ultimately reaches its highest point at 0.7993, with a loss of 0.6330 for the 45th epoch. The final accuracy of the model after 50 epochs is 0.7968, with a loss of 0.6232. This data may be used to assess the deep learning model's performance as it evolves and to spot patterns in training-related accuracy and loss. In Table 3, we can see the accuracy and loss table broken down by every five epochs.

Table 3: Loss and accuracy for each 5 epochs

Epochs	Accuracy	Loss
5	0.7930	0.6320
10	0.7880	0.6372
15	0.7918	0.6329
20	0.7930	0.6294
25	0.7968	0.6359
30	0.7930	0.6289
35	0.7918	0.6359
40	0.7943	0.6296
45	0.7993	0.6330
50	0.7968	0.6232

5. Discussion and Findings

We refined the experimental design based on the existing information in the literature. We adjusted the preprocessing pipelines and optimized the training-validation-test strategy for more stable results. While many earlier studies follow their own configuration, the present study used an updated technique by incorporating the stronger balancing, i.e., tuning and ensemble refinement, which enables us to obtain higher accuracy on the HAM10000 dataset.

In our study, we comprehensively compared the accuracy achieved by our proposed model with existing methods in the field. Our deep learning model exhibited an impressive accuracy of 79.6%, outperforming the accuracies reported by other research authors. The publications we examined demonstrated accuracies ranging from 71.7% to 75.03%. It is worth noting that many of these studies also utilized convolutional neural networks (CNNs), which align with our approach. These findings highlight the effectiveness of our model and its superior performance when compared to established methods in the domain.

Our work utilizes sophisticated deep-learning algorithms to contribute to skin categorization using dermoscopy skin images. The strength of our suggested model compared to current approaches is shown by a comparative study, which is presented in Table 4. Another study, Mporas et al. [28], achieved a 74.3% accuracy rate by integrating an ANN with machine learning (ML) on the HAM10000 dataset. A 75.03% accuracy rate was obtained by Hekler et al. [27] using CNNs on the HAM10000 dataset.

Table 4: Comparison of the proposed model's accuracy with the existing methods

Publications	Techniques	Datasets	Accuracy
Mporas et al. [28]	ML + ANN	HAM10000	74.3%
Hekler et al. [27]	CNN	HAM10000	75.03%
Our Method	CNN	HAM10000	79.6%

Our innovative method achieved an impressive 79.6% accuracy by relying only on CNNs on the HAM10000 dataset, resulting in a significant performance boost. This superior performance reflects how strong and effective our deep learning model is. Our technique demonstrates higher accuracy, highlighting the subtle architectural decisions and model improvements, even though this research often uses CNNs.

The results show that our suggested model is superior at differentiating various skin lesions, and not only does it compete well. In teledermatology, where accurate diagnosis and treatment depend on exact categorization, this higher level of accuracy is critical. Our study's results add to the ongoing scientific discussion on skin disease categorization and provide a potential answer with practical dermatological applications. Future studies should look at fine-tuning parameters and extending datasets to improve the model's resilience and generalizability.

The suggested deep learning model for teledermatology skin categorization has shown encouraging results. However, it does have certain limitations that should be taken into account. For successful training, CNNs rely heavily on big and varied datasets. Using the HAM10000 dataset in this research has its merits, but it may have drawbacks when it comes to representing specific demographics or kinds of skin lesions. Furthermore, the model's accuracy might be affected by differences in image quality, lighting, or ethnic skin types that aren't fully covered in the dataset. It is necessary to continuously improve the proposed CancerVisionNet to account for the complexity of real-world teledermatology situations. Improving the model's adaptability and reliability in various clinical contexts requires resolving these constraints.

6. Conclusion and Future Research Directions

The efficacy of CNNs in accurately classifying skin lesions has been shown in our research. By leveraging the HAM10000 dataset, we developed a method for diagnosing and categorizing seven distinct types of skin disorders with an accuracy of 80 percent on test data. Our findings suggest that CNNs are a promising tool for improving the accuracy and efficiency of skin cancer diagnosis, which can ultimately lead to better patient outcomes. To guarantee these models can be used in diverse patient groups and clinical contexts, further study is necessary to enhance their performance.

To further improve skin classification accuracy, future work should concentrate on making the suggested deep learning model more robust by adding multi-modal information, including patient history and clinical data. It may also be possible to increase the model's generalizability by investigating transfer learning approaches to modify it for use with other dermoscopic datasets other than HAM10000. Crucial to the success of teledermatology in the real world would be the incorporation of explainable AI approaches, which would allow doctors to see how the model makes decisions, increasing confidence and acceptance of the technology. Another interesting direction for future study is to see if the model can be used in edge computing contexts to help with real-time diagnostics and situations with limited resources. The overall objective is to improve automated disease categorization systems that are more complete, understandable, and widely used in teledermatology settings. These directions are in line with that aim.

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Conflict of Interests

Publication of this research article has no conflict of interest.

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