Semi-Automated Detection of Skin Cancer using Deep Learning and Weakly-Supervised Human Verification Techniques

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May 1, 2024

Abstract

This project aims to implement semi-automated system in digital image processing for early detection of cancerous or non-cancerous skin diseases with weakly human supervised verification techniques to reduce margin of error and improve accuracy. The system will analyze images of skin lesions captured through dermatoscopes. By performing image segmentation and feature extraction on the true region of interest verified by the experts, the system will be capable of accurately identifying potential abnormalities indicative of skin diseases providing users with timely insights for early intervention and medical consultation. The detection will be performed in two parts - (i) Whether the lesion detected at region of interest is malignant or benign (ii) If the detected region is benign what is the type of skin-cancer detected. Pre-trained ResNet50 model has been utilized for binary classification of data into benign and malignant, while CNN model is used for achieving the latter aim. For training the model HAM10000 ISIC dataset is used. The primary model has displayed an overall accuracy of 92 percent and f1 score of 0.92 and 0.91 for benign and malignant condition respectively with a high precision of 0.95 for malignant and 0.89 for benign respectively. The proposed system holds promise for improving the efficiency and accuracy of skin disease diagnosis, providing quick early detection mechanism of serious skin conditions raising awareness by accommodating timely medical intervention and diagnosis. .

1 Introduction

Skin cancer is a type of cancer that originates in the cells of the skin, which is the body's largest organ and serves as a protective barrier against environmental damage. It arises when skin cells undergo abnormal changes, leading to uncontrolled growth and potentially harmful tumors. Skin cancer is the most common type of cancer worldwide, and its incidence has been rising, largely due to increased exposure to ultraviolet (UV) radiation from sunlight and artificial sources such as tanning beds.

Understanding skin cancer requires a basic knowledge of skin structure. The skin has three primary layers:

1) Epidermis**:** The outermost layer, containing various types of cells, including keratinocytes (the most abundant) and melanocytes (responsible for skin pigment). 2)Dermis: The middle layer, containing connective tissue, blood vessels, nerve endings, and hair follicles. 3)Hypodermis (Subcutaneous Layer): The innermost layer, composed mainly of fat and connective tissue.

There are 4 major types of cancer which are listed as follows:-

1. Basal Cell Carcinoma (BCC): Basal cell carcinoma is the most common type of skin cancer, originating in the basal cells of the epidermis, the outermost skin layer. It typically presents as a pearly or waxy bump, a flat, flesh-colored or brown scar-like lesion, or a sore that bleeds and heals but recurs. BCC is usually slow-growing and rarely metastasizes, but it can cause significant local tissue damage if left untreated. Risk factors include prolonged UV exposure, fair skin, older age, and family history. Treatment often involves surgical excision, but other options like cryotherapy, curettage, or topical medications are also used depending on the lesion's size and location.

2. Squamous Cell Carcinoma (SCC): Squamous cell carcinoma arises from the squamous cells in the epidermis and is the second most common type of skin cancer. It typically appears as a firm red nodule, a flat lesion with a scaly crust, or a sore that doesn't heal. SCC can be more aggressive than BCC and has a higher potential to metastasize, especially if it arises on the lips, ears, or other high-risk areas. Risk factors include UV exposure, chronic skin injuries, certain chemicals, and

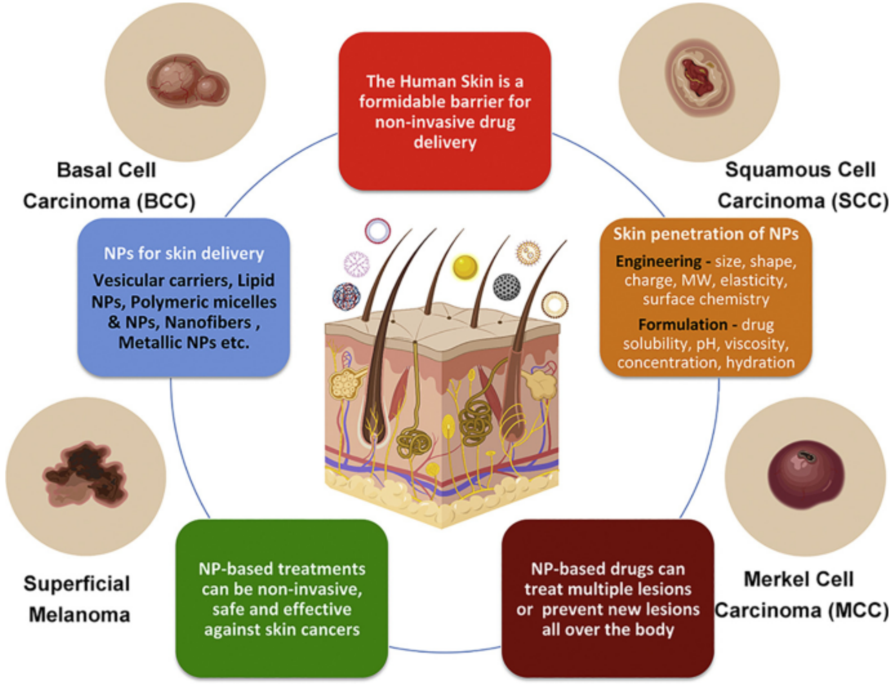

Figure 1: Types of Skin Cancer

immunosuppression. Treatment usually involves surgical excision, with more advanced cases requiring radiation or chemotherapy.

3. Melanoma: Melanoma is the most aggressive form of skin cancer, originating from melanocytes, the cells responsible for skin pigmentation. It often presents as an irregularly shaped and colored mole, or as a rapidly changing existing mole. Melanoma can metastasize quickly and is associated with a higher mortality rate if not caught early. Risk factors include UV exposure, fair skin, family history, and the presence of many or atypical moles. Early detection and treatment are crucial, with surgical excision being the primary treatment. Advanced cases may require chemotherapy, radiation, immunotherapy, or targeted therapy.

4. Merkel Cell Carcinoma (MCC): Merkel cell carcinoma is a rare and aggressive form of skin cancer that arises from Merkel cells, specialized skin cells involved in touch sensation. It often appears as a rapidly growing, painless nodule, typically on sun-exposed areas like the face, neck, or hands. MCC has a high risk of metastasis and is associated with older age, immunosuppression, and UV exposure. Treatment usually involves surgical excision with wide margins, followed by radiation therapy. Advanced cases may require chemotherapy or immunotherapy.

1.1 Difficulties faced while primary detection of skin-cancer

One of the primary difficulties in detecting skin cancer is its resemblance to benign skin conditions. Early-stage skin cancers can look like harmless moles, warts, freckles, or other skin irregularities. This similarity can lead to delays in diagnosis, as people might not recognize the signs of a potentially serious condition. For instance, basal cell carcinoma might appear as a simple flesh-colored bump or a pinkish patch, similar to common moles or skin tags. Melanoma, a more aggressive type of skin cancer, can mimic normal moles, leading to underestimation of its severity. Diagnosis of skin cancer often relies on the experience and expertise of dermatologists who perform visual examinations. This reliance on human judgment introduces an element of subjectivity, as different clinicians might have varying levels of expertise or may interpret lesions differently. Factors like lighting, patient skin tone, and lesion location can influence the visual assessment, leading to misinterpretation or missed diagnoses. This subjectivity necessitates the use of advanced tools like dermatoscopes, but even with such tools, the human element can lead to inconsistent results. Skin cancers can manifest in a wide variety of forms, colors, sizes, and textures, further complicating detection. This variability makes it challenging to establish clear diagnostic criteria. For example, melanoma can appear as a dark or irregularly shaped mole, but it can also be amelanotic (lacking pigment), appearing more like a flesh-colored bump or sore. Similarly, squamous cell carcinoma might look like a scaly patch, a wart-like growth, or a firm red nodule. The range of presentations means that clinicians must be vigilant and consider a broad differential diagnosis.

1.2 How can Deep-Learning and Semi-Automated Techniques Help?

Deep learning and semi-automated techniques have transformed the landscape of medical diagnostics, particularly in the field of skin cancer detection as we can observe in paper[5]. Deep learning models, a subset of artificial intelligence (AI), are capable of recognizing patterns in complex data sets. In the context of skin cancer, these models are trained on vast databases of labeled images, encompassing various types of skin lesions, including benign and malignant ones. By identifying subtle differences in texture, color, shape, and size, these models can classify lesions with a high degree of accuracy which has been perfectly demonstrated by paper [6]. Deep learning models can distinguish between different types of skin cancer (such as basal cell carcinoma, squamous cell carcinoma, and melanoma) and benign lesions with a high level of accuracy. This capability provides valuable diagnostic support to dermatologists, potentially reducing the risk of oversight or misdiagnosis.

These models can serve as a "second opinion," offering an additional layer of validation for clinical diagnoses[9]. This can be especially useful in complex cases where visual examination alone might be inconclusive. Early detection is crucial for successful skin cancer treatment[7]. Deep learning algorithms can analyze changes in skin lesions over time, enabling earlier identification of potential cancers. With the ability to analyze large volumes of data quickly, deep learning models can identify early signs of aggressive cancers like melanoma, potentially catching them before they become more severe. Subjectivity in visual examination can lead to variability in diagnosis and treatment recommendations[8]. Semi-automated techniques offer a more standardized approach, minimizing the impact of human error[10]. By using consistent criteria for lesion analysis, semi-automated techniques reduce subjectivity in diagnosis. This helps ensure that all lesions are evaluated based on the same metrics, leading to more reliable results. These techniques can help prioritize cases that require immediate attention, reducing diagnostic bottlenecks and allowing dermatologists to focus on high-priority cases. This streamlining can improve efficiency and reduce the risk of delayed treatment.

These models can analyze thousands of images in a fraction of the time it would take a human, providing rapid results that help reduce patient wait times and increase throughput. Deep learning models can improve over time by learning from new data and adapting to evolving diagnostic criteria. This continuous learning ensures that the models remain relevant and accurate as medical knowledge advances. Semi-automated techniques can not only analyze images but can also integrate other clinical data to provide comprehensive decision support for medical professionals. These systems can combine image analysis with other clinical information, such as patient history, risk factors, and laboratory results. This holistic approach helps clinicians make more informed decisions about diagnosis and treatment. Semi-automated techniques can assist in recommending additional diagnostic steps, such as biopsies, based on the analysis of lesion characteristics. This guidance can help clinicians determine the most appropriate course of action for each patient.

2 Related Works

Several researchers and organizations have contributed to the development of computer vision systems for the detection of skin diseases. We can see some of the noteworthy researches such as in paper [1], a deep learning model is trained on a large dataset of skin lesion images. The model achieved performance comparable to dermatologists in classifying skin lesions into malignant and benign categories. It demonstrated the potential of deep learning algorithms in assisting dermatologists with accurate diagnosis. While the model showed promising results, its generalization to diverse populations and real-world clinical settings might be limited. Further validation on larger and more diverse datasets is necessary to assess its robustness.

Paper [2] discussed the results of the ISBI 2016 Challenge on skin lesion analysis for melanoma detection. Various computer vision approaches were evaluated for tasks such as lesion segmentation, feature extraction, and classification. The challenge facilitated the benchmarking of different methods and highlighted the state-of-the-art in skin disease detection. However, the challenge datasets may not fully represent the diversity of real-world clinical cases, potentially limiting the generalizability of the findings. Moreover, the challenge's focus on melanoma detection may overlook other important skin diseases.

In paper [3], a deep learning model based on very deep residual networks for automated melanoma recognition in dermatoscopy images is introduced. The model achieved high accuracy in distinguishing between melanoma and benign lesions, surpassing previous methods. It demonstrated the effectiveness of deep residual networks in improving the performance of computer-aided diagnosis systems for melanoma detection. Yet, its primary drawback is the reliance on dermatoscopy images, which may limit the model's applicability to settings wheredermatoscopes are not available. Additionally, the performance of the model on diverse skin types and lesion types warrants further investigation.

This study in paper [4] proposed a deep learning approach for skin cancer detection, focusing on integration regions of interest (IROIs) to improve model performance. By aggregating predictions from multiple regions within a lesion, the model achieved higher sensitivity and specificity compared to traditional approaches. The research highlighted the importance of considering spatial information in skin lesion analysis for enhanced diagnostic accuracy. However, it must be noted that the manual selection of IROIs introduces subjectivity and may require expertise, potentially hindering the model's usability in real-world clinical practice. Moreover, the study's findings need validation on larger and more diverse datasets to assess generalizability.

3 Methodology

Our model is designed in 5 phases as follows: -

A. Collection of datasets: For the purpose of training the models, a large dataset HAM10000 ISIC is used. B. *Model 1:* This a Resnet50 model used for training dataset for the classification of dermoscopic images into malignant and benign conditions. C. *Model 2:* This is a CNN based model which is trained to be used for categorizing the dermoscopic images into 7 different types of cancer. D. An elementary website will be created having HTML,CSS and Javascript as its front-end, for authenticating the user. The user interface is planned to have 2 separate sections - a) For General Users b) For medical Professionals. The medical professionals will be provided the additional flexibility to manipulate the region of interest to improve the specificity of ground truth. This will allow application of semi-automated weakly supervision facilitating to maximize accuracy and minimize error. E. Finally, both the models along with the frontend will be integrated using a python-based back-end environment, preferably Flask.

Ultimately, the website will allow the user to upload dermatoscopic image and is expected to provide highly acurate predictions about the type and possibility of skin-cancer.

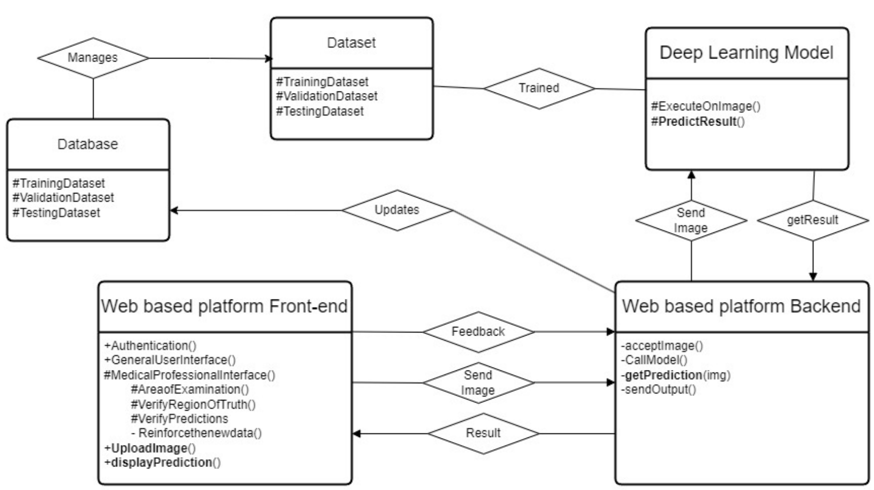

Figure 2: Design Architecture

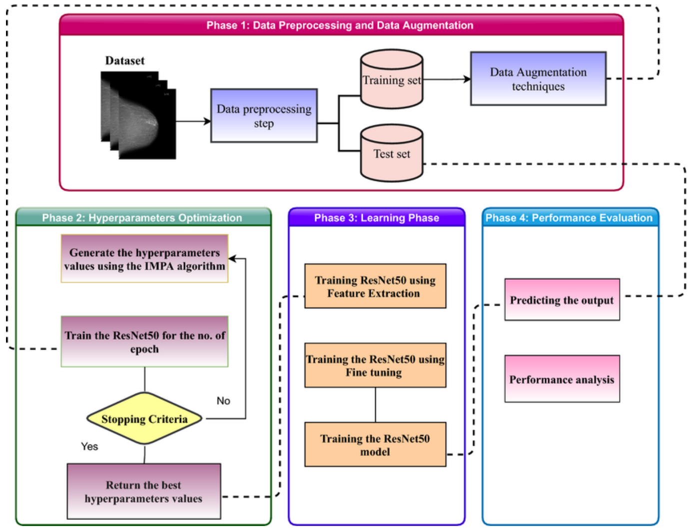

Figure 3: Resnet50 layers

3.1 Model 1: Resnet50

For the primary binary classification of image into benign and malignant we have employed pre-trained ResNet50 model. ResNet50 is a deep learning architecture that has gained popularity for its effectiveness in image classification tasks, including the classification of skin cancer images into benign and malignant. This model is part of the ”Residual Network” (ResNet) family, designed by Microsoft Research, and it addresses one of the key challenges in deep neural networks—vanishing gradients. ResNet50 is a deep convolutional neural network with 50 layers, designed to overcome the problem of vanishing gradients through the use of residual connections. These connections allow gradients to propagate more effectively through the network, enabling the training of deeper networks without significant degradation in performance.

The defining feature of ResNet is the use of residual blocks, which contain skip connections that bypass certain layers. This architecture allows the network to learn identity mappings more easily, thereby mitigating vanishing gradient issues. ResNet50 has multiple convolutional layers with varying kernel sizes, allowing it to capture different levels of features from the input images. To maintain efficiency, ResNet50 uses a bottleneck structure, where 1x1 convolutional layers are used to reduce the dimensionality of the feature maps, followed by 3x3 convolutions, and then another 1x1 layer to restore the dimensionality. Batch normalization helps stabilize training by reducing internal covariate shift, while ReLU activation introduces non-linearity, which is essential for learning complex patterns. Thus, ResNet50 is a prefered choice for binary classification of dermoscopic images into malignant and benign. The following figures show the results obtained from training the Resnet50 model.

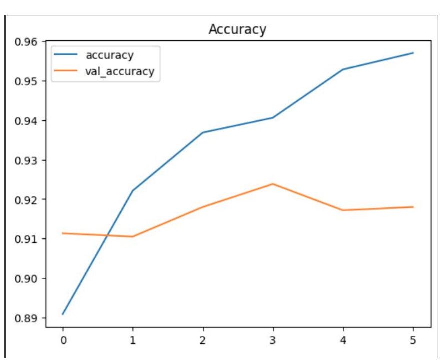

Figure 4: Accuracy

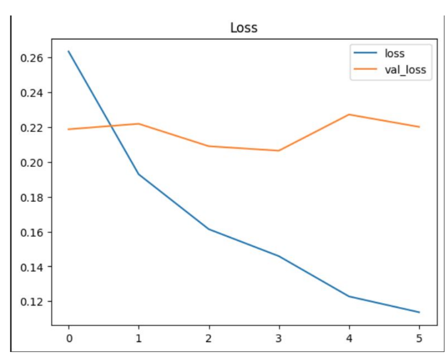

Figure 5: Loss

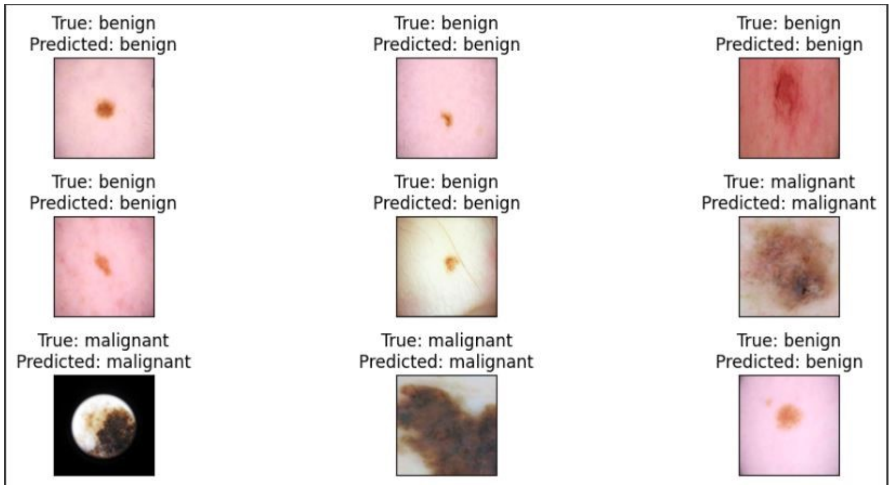

Figure 6: Predictions made by the Resnet model

3.2 Model 2: CNN (Convoluted Neural Network)

A Convolutional Neural Network (CNN) is a type of deep learning algorithm designed for processing structured grid-like data, such as images. CNNs are widely used in image classification, object detection, and various other computer vision tasks. They are particularly effective at extracting hierarchical features from images, making them ideal for categorizing skin cancer images. CNNs are neural networks that use convolutional operations to process data, allowing them to automatically and adaptively learn spatial hierarchies of features. They are characterized by their use of convolutional layers, which apply filters to the input data, and pooling layers, which reduce the dimensionality of the data while retaining key features.

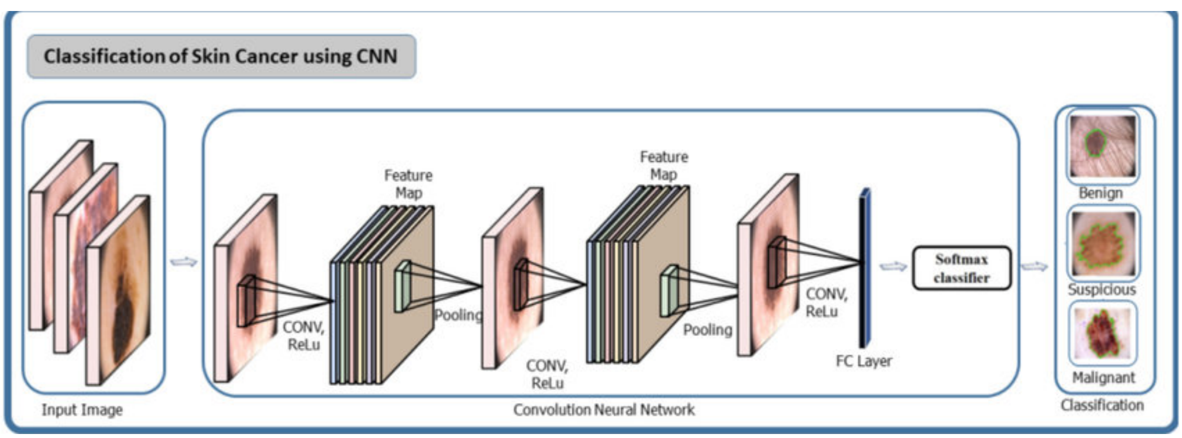

Figure 7: Layers of CNN

CNNs typically consist of the following types of layers:

1. Convolutional Layers: These are the core building blocks of CNNs. Each convolutional layer contains a set of filters (also known as kernels) with learnable parameters. The filters slide over the input data with a specific stride, applying a convolution operation at each step. This operation involves taking the dot product between the filter and a region of the input, then summing the result to produce a feature map. The output of a convolutional layer is a set of feature maps, where each map represents a specific feature detected by a filter. As the network grows deeper, these feature maps represent increasingly complex patterns and abstractions.

2. Activation Layers: Activation layers introduce non-linearity into the network, which is crucial for deep learning models to learn complex patterns. Without activation functions, a CNN would

behave like a linear model, incapable of capturing the intricacies of real-world data. ReLU is the most common activation function in CNNs. It is defined as $f(x)$=max(0,x), meaning it outputs the input if it's positive and zero otherwise. ReLU's simplicity and efficiency make it a popular choice, reducing the risk of vanishing gradients.

3. Pooling Layers: Also known as subsampling or downsampling layers, pooling layers reduce the spatial dimensions of the feature maps, typically by taking the maximum value (max-pooling) or the average value (average-pooling) within a defined window, allowing for dimensionality reduction while retaining important features. This process helps control overfitting, reduce computational complexity, and increase translational invariance.

4. Fully Connected (Dense) Layers: Fully connected layers are typically found at the end of the CNN and are responsible for mapping the extracted features to the output classes. These layers are "fully connected" because each neuron is connected to every neuron in the previous layer. In classification tasks, the final fully connected layer typically uses a softmax activation function, which produces a probability distribution over the output classes. In binary classification tasks, a sigmoid activation is used to output a probability between 0 and 1.

5. Normalization Layers: Normalization layers aim to stabilize the training process by reducing internal covariate shift (the tendency of data distributions to change during training). These layers are commonly used to improve convergence and speed up training.

Results of training the model:

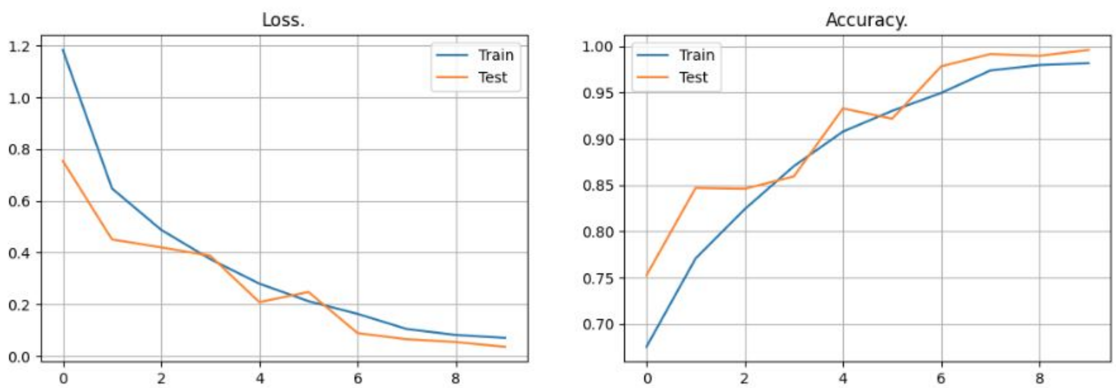

Figure 8: Loss and accuracy obtained through CNN

3.3 Implementation of Weakly Supervision in the User Interface

At the beginning, the user will authenticate oneself into the application. There will be two separate interfaces available - 1) For General Users 2) For Medical Professionals. A general user can upload dermoscopic images and get predictions like any other automated prediction systems. This model however, provides a premium facility for medical professionals who need to authenticate themselves using their medical registration numbers. The professional experts will be able to manipulate the area of examination on the dermoscopic image in the interface which will play a significant role in improving the ground truth and thus enhancing the accuracy of the output of the machine learning model. The professionals will also be provided a feedback to rate the accuracy of the model and give informative inputs and suggestions. For erroneous results, they can provide the correct diagnosis in the feedback. The data collected from these feedbacks from hundreds of medical practitioners worldwide, will result in an even better reinforcement of the models leading to an exponential improvement in the accuracy of the model overtime. Thus, this application will serve as a collaborative initiative to give importance to the knowledgeable experience of the medical practitioners.

4 Conclusion

While computer vision-based detection of skin diseases holds promise, several limitations and future directions warrant consideration. The generalizability of models across diverse populations and skin types remains a challenge. Current datasets may not adequately represent the full spectrum of skin diseases or variations in skin pigmentation, leading to potential biases and reduced performance in real-world applications. The interpretability of deep learning models poses a significant hurdle. Understanding the rationale behind model predictions is crucial for building trust among healthcare professionals and patients. Developing transparent and interpretable models will be essential for widespread adoption in clinical practice. The integration of computer vision systems into existing healthcare workflows requires careful consideration of regulatory, ethical, and privacy concerns. Ensuring compliance with data protection regulations and addressing potential biases in algorithmic decision-making are imperative.

Future research should focus on addressing these challenges by collecting more diverse and representative datasets, developing interpretable models, and establishing robust evaluation frameworks. Collaborative efforts between academia, industry, and healthcare providers are essential to advancing the field and realizing the full potential of computer vision in skin disease detection. Additionally, exploring novel applications such as real-time monitoring and telemedicine can further enhance accessibility and effectiveness in skin health management.

5 References

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