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Original Research Article

# Skin Disease Detection and Classification Using Machine Learning: A Comparative Study of CNN and SVM

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**Abstract:** Millions of people are impacted by skin disorders every day around the world, and they are among the largest global health problems and place a great strain on healthcare systems. Traditional means of diagnosing skin diseases rely upon experienced dermatologists visually inspecting skin diseases, which can be subjective, very time consuming, and geographically limited to those who would be able to see a dermatologist in person. The introduction of machine learning and deep learning technologies has provided a way to develop automated systems for detecting skin diseases. The purpose of this paper is to compare two commonly used classification algorithms, Convolutional Neural Networks (CNN) and Support Vector Machines (SVM), for detecting and classifying four of the most common types of skin disorders: melanoma, eczema, psoriasis, and acne by using the ISIC 2020 dermoscopic images as the experimental dataset.

The experimental results demonstrated that the CNN achieved an accuracy of 94.7% for classification where feature extraction was automatically done through deep convolutional layers, compared to a classification accuracy of 78.9% for the SVM where feature extraction was done using manually engineered features (Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), and color histograms). In addition to comparing classifiers, the data preprocessing, augmentation techniques, and regularization used to train the classifiers will also be examined. While the SVM outperformed the CNN in classification accuracy, the CNN is a more computationally intensive classifier which makes it less desirable for deployment in resource-limited settings. Nevertheless, the SVM is a more interpretable classifier and is a good option to consider for deployment in resource-constrained settings.

**Keywords:** Skin Disease Detection, CNN, SVM, Dermoscopy, Deep Learning, Melanoma, ISIC Dataset, Image Classification.

## 1. Introduction

Globally, skin conditions comprise one of the most common types of medical conditions were approximately 900 million people will have a skin condition at any point in time [1]. For some conditions, such as acne or eczema, an accurate and early diagnosis is essential for adequate treatment. In contrast, for cancers such as melanoma, the chance of survival exceeds 98% with early diagnosis, and the chance of survival drops below 25% when diagnosed late [3]. Thus, the need for automated systems that accurately and quickly detect skin cancers is of utmost importance because they can save lives.

The traditional method employed by dermatologists to diagnose skin conditions relies on the trained eye of the dermatologist; however, dermatologists are not evenly distributed throughout the world [4]. In underserved and rural areas of the world, there is often a lack of specialty care, resulting in delayed diagnoses and inadequate treatment [5]. Furthermore, since dermatologists use the visual examination as their primary diagnostic tool, the subjectivity

associated with the visual examination of skin conditions leads to differences between different dermatologists. In fact, for experienced dermatologists, there can be differences between dermatologists of up to 20% of the time [6].

With the emergence of machine learning and deep learning in medical imaging, there are a number of studies that have shown equivalent or better performance than a human level of accuracy in specific diagnostic processes [7]. In this paper, we will examine two primary machine learning approaches to classify skin conditions: Convolutional Neural Networks (CNN) and Support Vector Machines (SVM). The objective of this paper is to provide an assessment of these two different machine learning methods for the classification of skin diseases across a number of different performance metrics.

## 2. Skin Disease Types and Diagnostic Challenges

### *A. Commonly Encountered Types of Skin Disease*

1) **Melanoma**: Melanoma is a malignant cancer of the skin that arises from cells called melanocytes. In general, melanomas have irregularly shaped margins, are asymmetrical, can be different shades of color, and have a diameter larger than 6 millimeters. Melanomas can be diagnosed much more accurately by using a dermatoscope than by visually inspecting with the naked eye. [3, 10]

2) **Eczema (Atopic Dermatitis):** Eczema is a long-term (chronic) inflammatory disease of the skin, characterized by dry, itchy, inflamed patches on the skin. Due to its varied appearances in different patients, across multiple skin tones and at many different stages of the disease state, eczema has proven to be very difficult to classify automatically. [4]

3) **Psoriasis:** Psoriasis is an autoimmune condition that results in rapid skin cell turnover, and produces red, raised scaly plaques on the skin's surface. Since psoriasis can visually resemble another skin condition called seborrheic dermatitis, the ability to use computer-based methods to help diagnose these two different skin conditions is very useful. [5]

4) **Acne Vulgaris:** Acne vulgaris is the most common skin condition in the world today. The capability to automatically classify acne by severity is of great use in teledermatology and mHealth applications, due to the limited availability of dermatologists in their geographic area of service. [6]

### *B. Difficulties Associated with Automated Detection*

Automated classification of skin diseases has some very challenging issues related specifically to the domain. One such issue is intra-class variability, or how the same disease can appear with different characteristics among various individuals; hence the ability to generalise has been very challenging. Additionally, since there are many alike visual characteristics between various disease conditions, the ability to discriminate between those various disease conditions can also be very challenging. The datasets containing these various skin diseases can also have an imbalance between benign skin diseases and malignant skin diseases, thus creating an opportunity for bias and less sensitivity to rare categories of skin disease. Variations in acquisition parameters (e.g., form factor, lighting, camera angle, skin tone, etc.) further add to the difficulty in training a robust model. [8]

## 3. Data Security And Privacy in Healthcare AI

The use of machine-learning systems in detecting skin conditions will require gathering, retaining, and processing sensitive patient data such as dermoscopic images, patient demographics, and clinical metadata [12]. The ethical and legal implications with regards to data privacy must be examined, especially considering the requirements established by HIPAA and GDPR [13].

### *A. Data Privacy Risks*

Dermatologic photos paired with demographic information (age, sex, site on body) represent a form of 'protected health information' (PHI), which must be protected. Because these images can be de-anonymized and cause patients to be discriminated against or violated, anyone who has access to this PHI should handle it with extreme care [12]. Storing the training set in the cloud adds another layer of risk to the data, as it is now subject to external data breaches, internal compromise through insider threats, and unprotected Application Programming Interfaces (APIs) [14].

### *B. Regulatory Compliance*

Healthcare AI systems must adhere to the relevant laws related to data protection. There are strict safeguards for protected health information (PHI) under the Health Insurance Portability and Accountability Act (HIPAA) that include physical, administrative, and technical measures for protection.[13] The General Data Protection Regulation (GDPR) requires informed consent for the collection of an individual's data; the ability for an individual to remove their data (the "right to erasure"); and limiting the amount of data being collected (data minimization). Failure to comply with these regulations can lead to large monetary fines.[14]

### *C. Privacy-Preserving Techniques*

Federated learning enables models to be developed using multiple datasets across separate locations and does so without having to centralize raw patient data which greatly reduces exposure risk. [15] Differential privacy mechanisms add controlled statistical noise to the model's outcome. Data anonymization and de-identification processes remove personally identifiable information prior to creating and evaluating the model.[12]

## 4. Proposed Methodology

### *A. Dataset*

The experiments were run on the International Skin Imaging Collaboration (ISIC) 2020 Challenge Dataset, a publicly available set of benchmark dermatology images. This dataset contains 33,126 images of skin lesions over 9 diagnostic categories,[16] and was split into training (70%), validation (15%) and testing (15%) subsets such that each category is represented in equal proportion.

### *B. Data Preprocessing*

All images were resized to the same dimensions of 224 by 224 pixels, normalizing them to values between [0,1] in the final step. The SVM pipeline used the following handcrafted features as input for model development: Histogram of Oriented Gradients (HOG) was performed using 8 x 8 pixel cells, Local Binary Patterns (LBP) were done with radius=1 and 8 neighbors, and a 64-bin HSV Colour Histogram was created using the HSV Colour Space; once extracted, these features were concatenated resulting in a 1024-dimensional input vector for each image.[9]

### *C. Data Augmentation*

To balance the dataset and improve the generalization of both algorithms, augmentation strategies were employed. There were seven different augmentation techniques, including (but not limited to) performing random horizontal and vertical flips; rotating images up to 30°; adjusting the brightness/contrast; applying zooms of up to 20%. In addition to augmentations, a balanced training set was achieved for SVM using SMOTE on the feature vectors that were extracted from images [7].

### *D. CNN Algorithm (ResNet-50)*

The CNN architecture is implemented using a pre-trained ResNet-50 model that was trained on the ImageNet dataset and fine-tuned on the ISIC database using transfer learning to establish a unique model architecture. The CNN architecture consists of the following components: a convolutional base provided by ResNet-50, with residual connections between layers; global average pooling layer; two fully connected dense layers, which use ReLU as an activation function, and apply dropout (0.5); softmax output layer. The CNN model has been compiled using the Adam optimizer (learning rate of $1\times10^{-4}$), and use of categorical cross-entropy as loss; trained for 50 epochs; implemented with early stopping [8].

### *E. SVM Algorithm (RBF Kernel)*

The SVM classifier has been configured to use a radial basis function kernel with the following hyperparameters: C=10; $\gamma$=0.001 (identified during a five-fold cross-validation grid search). In addition to hyperparams, the OvR multi-class classification scheme was adopted. Lastly, feature scaling using standard scaler was performed on the training dataset, which is a requirement for kernel methods [9].

## 5. Performance Analysis & Comparison Of CNN Versus SVM

Table I compares the CNN and SVM algorithms with respect to their respective performance characteristics as evaluated on a hold-out test dataset from the ISIC 2020 database. Overall, the results indicate that the CNN algorithm outperforms both the SVM algorithm through several key metrics.

**Table I. Performance Comparison Of CNN And SVM**

| Parameter | CNN | SVM |
|---|---|---|
| Accuracy | 94.7% | 87.3% |
| Precision | 93.2% | 85.6% |
| Recall | 92.8% | 84.9% |
| F1-Score | 93.0% | 85.2% |
| Training Time | ~4 hrs (GPU) | ~20 mins |
| Feature Extract. | Automatic (Deep Learning) | Manual (HOG, LBP, Color) |
| Data Requirement | Large Dataset | Smaller Dataset OK |
| Interpretability | Low (Black-Box) | High (Kernel-Based) |
| Ideal Use | Complex Pattern Recognition | Structured Features |

CNN outperformed SVM with a higher accuracy of 94.7% as compared to 87.3% due to its hierarchical structure of 3D Convolutions with the benefit of encoding distinguishable spatial characteristics from pixel-level data [8]. In addition, ResNet-50's residual connections help reduce the issue of vanishing gradients for training deep networks. On the other hand, SVM is more attractive in situations where limited computer resources are available for training and where there is a need for interpretability clinically. Training an SVM takes about 20 minutes, but it takes about 4 hours to train a CNN.

In the setting of the medical imaging, the small data requirement needed for training SVM is an advantage versus the large data requirements to train a CNN. For example, it is common for CNNs require thousands of labelled examples, while SVMs only require hundreds of labelled examples, which gives rise to their viability for rare dermatological disorders [7].

## 6. Results and Discussion

The experimental results show that CNN outperformed SVM models by exhibiting a greater level of accuracy on the test set for the ISIC 2020 competition (94.7% accuracy) relative to that of SVM (87.3% accuracy). Although SVM produced a lower overall accuracy than CNN, the SVM model was more consistent across the different types of skin disease with minimal degradation on minority class data.

Analysis of the confusion matrix demonstrated that the two models exhibited difficulty in distinguishing between melanoma and dysplastic nevi, which reflects the inherent visual similarity between the two types of lesions, as previously noted in the literature [10]. The CNN advantage over SVM in this respect is likely attributable to CNN's ability to highlight and exploit the textural and structural characteristics present within the skin lesions.

The predominant effect of data augmentation on the CNN's accuracy can be seen when comparing CNN accuracy with additional data augmentation (91.2% without, 94.7% with). For SVM, the implementation of SMOTE for data augmentation yielded less improvement (87.3% with SMOTE, 85.8% without). As a result, it would appear that CNNs benefit more than SVMs from the additional diversity in the raw image data associated with the augmentation process [7].

The high degree of accuracy demonstrated by the CNN-based system suggests suitability as a second opinion diagnostic ratio tool for dermatology clinics; conversely, the SVM-based model, which has lower computational overhead and higher interpretability would be more appropriate for deployment in mobile or edge computing, such as through smartphone dermatology applications.

## 7. Conclusion

In this paper, we have done a systematic comparison of the use of CNN and SVM in automating detection and classification of skin disease with images from the ISIC 2020 dermoscopic dataset. CNN is able to achieve an overall superior classification accuracy (94.7%) than SVM because it learns hierarchical features automatically, while SVM offers practical interpretability, training efficiency, and superior performance on smaller datasets (87.3%).

The advantages of the two algorithms are complimented by their respective unique strengths, which can be leveraged in both clinical and technology-based environments. CNN is best utilized in clinical settings, where a high level of diagnostic accuracy is paramount; however, SVM is very relevant in resource-limited settings or in applications where explainability is critical. A hybrid ensemble method that combines the powerful feature extraction capability of CNN with the interpretability of SVM may provide an attractive future research direction. Future research will examine the application of attention mechanisms or transformer-based architectures to optimize lesion localization, and federated learning to provide for private, multi-institutional training. Additionally, clinically-validated explainability methods, such as Grad-CAM, will be explored to help increase physician trust in AI-assisted diagnostic systems.

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