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Comparative Analysis of CNN and CNN-SVM Methods For Classification Types of Human Skin Disease

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Abstract: Cancer is one of the leading causes of death worldwide, with skin cancer ranking fifth. The skin, as the outermost organ of the body, is susceptible to various diseases, and accurate diagnosis is crucial for effective treatment. However, limited access to dermatologists and expensive skin biopsies poses challenges in achieving efficient diagnosis. Therefore, it is important to develop a system that can assist in efficiently classifying skin diseases to overcome these limitations. In the field of skin disease classification, Machine Learning and Deep Learning methods, especially Convolutional Neural Network (CNN), have demonstrated high accuracy in medical image classification. CNN's advantage lies in its ability to automatically and deeply extract features from skin images. The combination of CNN and Support Vector Machine (SVM) offers an interesting approach, with CNN used for feature extraction and SVM as the classification algorithm. This research compares two classification methods: CNN with MobileNet architecture and CNN-SVM with various kernel types to classify human skin diseases. The dataset consists of seven classes of skin diseases with a total of 21.000 images. The results of the CNN classification show an accuracy of 93.47%, with high precision, recall, and F1-score, at 93.55%, 93.74%, and 93.62%, respectively. Meanwhile, the CNN-SVM model with "poly," "rbf," "linear," and "sigmoid" kernels exhibits varied performances. Overall, the CNN-SVM model performs lower than the CNN model. The findings offer insights for medical image analysis and skin disease classification research. Researchers can enhance CNN-SVM model performance with varied kernel types and techniques for complex feature representations.

Keywords: Convolutional Neural Network (CNN), Dermatological, MobileNet architecture, Skin disease classification and Support Vector Machine (SVM)

INTRODUCTION

Cancer is one of the leading causes of death worldwide, accounting for approximately 10 million deaths each year. About 1 in 6 deaths globally is attributed to cancer. Cancer-related deaths are projected to increase by 45% between 2008 and 2030. Skin cancer ranks fifth as the most common form of cancer. Abnormal growth of skin cells leads to skin cancer, making it one of the most prevalent types of cancer worldwide (Ünver & Ayan, 2019). The skin is a crucial part of the body as it serves as the outermost layer, protecting the entire human body. It consists of three layers, namely the outermost layer (epidermis), the layer beneath the epidermis (dermis), and the innermost layer of the skin (hypodermis). The skin plays a role in temperature regulation, immune defense, vitamin production, and sensation.

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Being the outer physical protector of the body, the skin plays a vital role in safeguarding against exposure to ultraviolet rays and harmful chemicals. The skin also possesses antibacterial functions that contribute to the immune system's ability to combat foreign substances and harmful microorganisms. However, as an exposed organ, the skin is susceptible to disease attacks. Numerous external and internal factors can influence the occurrence of skin diseases, such as environmental hygiene, individual immune systems, and lifestyle. Skin diseases can be caused by skin damage due to fungal growth, hidden bacteria, allergic reactions, microorganisms affecting skin texture, or pigment production (Refianti et al., 2019). Skin diseases come in various types, forms, and causes. Some common types of skin diseases include Actinic Keratoses and Intraepithelial Carcinoma (AKIEC), Basal Cell Carcinoma (BCC), Benign Keratosis-like Lesions (BKL), Dermatofibroma (DF), Melanocytic Nevi (NV), Melanoma, Vascular Lesions (VASC), and others.

Accurate diagnosis of skin diseases is typically done by dermatology experts, but challenges like limited access to specialists and low awareness about skin health are common. Untreated skin diseases can lead to disabilities, high treatment costs, and even threaten life. Dermatologists often use skin biopsies for diagnosing chronic skin diseases, but this can be expensive and cause wounds (Tschandl et al., 2018). Hence, an efficient system for classifying skin diseases is essential to overcome these limitations.

Computer vision, a branch of artificial intelligence, has revolutionized healthcare by enabling computers to analyze medical image data for diagnosis (Kose & Alzubi, 2021). Convolutional Neural Network (CNN), a popular Deep Learning technique, has shown promising results in image classification, especially in medical imaging (Gong et al., 2019).

CNN has shown high accuracy in medical image classification, such as studies conducted by (Mukkapati & Anbarasi, 2022), (Kassem et al., 2020), (Al-masni et al., 2020), (Chaturvedi et al., 2020) and (Deif & Hammam, 2020). Owing to its ability to automatically extract features from skin images and classify various types of skin diseases accurately. However, it has limitations, such as the need for a large and representative dataset and long training times. The combination of CNN-SVM provides an intriguing approach, utilizing CNN for feature extraction and SVM for classification. However, in classifying types of skin diseases using CNN and CNN-SVM, several issues need to be addressed. These issues include the need for a sufficiently large and representative dataset, class imbalance between the number of samples for different skin disease types, data preprocessing complexity, and the development of more efficient CNN architectures.

This research aims to compare the performance of two classification methods, namely Convolutional Neural Network (CNN) and the combination of Convolutional Neural Network - Support Vector Machine (CNN-SVM), in multi-class classification of skin diseases. The main objective is to analyze the classification results based on accuracy, precision, and recall from both models. Additionally, this study will analyze the strengths and weaknesses of each method to provide a deeper understanding of the utilization of CNN and CNN-SVM in skin disease classification. The expected outcome of this research is to improve the accuracy and reliability of multi-class skin disease classification using CNN and CNN-SVM, and to make a significant contribution to the development of diagnostic solutions in the medical field.

LITERATURE REVIEW

A study by (Keerthana et al., 2023) aimed to automatically classify dermoscopy images as benign or melanoma lesions using a hybrid CNN-SVM model. The study compared CNN combined with three Machine Learning methods: SVM, KNN, and DT. Results showed that CNN-SVM achieved higher accuracy compared to CNN-KNN and CNN-DT. The research also compared various CNN architectures, including AlexNet, GoogleNet, VGG-16, VGG-19, ResNet-18, ResNet-50, ResNet-101, ShuffleNet, MobileNet, and DenseNet-201. The final results indicated that using CNN-SVM with

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combined transfer learning achieved 87.43% accuracy for DenseNet201-ResNet50 and 88.02% for DenseNet201-MobileNet. However, the study only classified 2 types of diseases, suggesting potential for improvement to classify a greater variety of diseases.

Another study by (Yanagisawa et al., 2023) focused on developing a Convolutional Neural Network (CNN) based model and computer-aided diagnosis (CAD) system for skin image segmentation to create a suitable dataset for CAD with multiple skin disease classifications. The CNN segmentation model was capable of automatically extracting skin lesions and separating them from the image background, achieving sensitivity and specificity of around 90% in distinguishing atopic dermatitis. However, the dataset had variations and differences in image domains, which can pose challenges for the model in recognizing and distinguishing important features in the images. Therefore, using datasets with differences in image domains for skin disease classification is not recommended.

In another study by (Aljohani & Turki, 2022), Deep-CNN was used to automatically classify skin melanoma cancer from skin lesion images. Various CNN architectures, such as DenseNet201, MobileNetV2, ResNet50V2, ResNet152V2, Xception, VGG16, VGG19, and GoogleNet, were tested. Although the GoogleNet architecture showed the best performance, the study was focused on only one type of skin disease, melanoma, and there was no explanation regarding the effectiveness of this architecture in recognizing different features, different skin types, and various disease types. The accuracy obtained was relatively low, with training at 74.91% and testing at 76.08%, indicating the need for further improvements.

A study conducted by (Akter et al., 2022) aimed to perform multi-class skin cancer classification using the Deep Convolutional Neural Network method. The study applied the CNN model and 6 transfer learning models, namely Resnet-50, VGG-16, Densenet, Mobilenet, Inceptionv3, and Xception, to the benchmark HAM10000 dataset with 7 types of skin diseases. The results obtained accuracy percentages of 90, 88, 88, 87, 82, and 77 for inceptionv3, Xception, Densenet, Mobilenet, Resnet, CNN, and VGG16, respectively. However, the study did not specify the augmentation results specifically, only mentioning the augmentation was done on the overall data. Additionally, some of the classified skin disease types had limited datasets, suggesting the need for augmentation to balance the data. Imbalanced datasets can lead to biases towards the majority class, affecting accuracy results.

In the research conducted by (Srinivasu et al., 2021), a computerized process was proposed to classify skin diseases using MobileNet V2 and Long Short-Term Memory (LSTM) based Deep Learning on the HAM1000 dataset. LSTM was used to process feature sequences extracted by CNN. As the images were taken at different times but were still within the same category, there was no specific need to consider temporal sequences in the CNN-LSTM approach. The CNN-SVM approach was more suitable for clustering data with nonlinear decision boundaries (feature-class relationships), and SVM could handle multi-class classification problems effectively.

Another multi-class study by (Junayed et al., 2021) employed the Deep Convolution Neural Network (CNN) method to detect and classify 4 types of skin cancer. The proposed model achieved an accuracy of 96.98% for the four types of skin cancer. However, the study used a relatively small initial dataset of 800 images for 4 disease types, indicating the need for dataset augmentation to learn more representative features and differentiate between disease classes.

(Chaturvedi et al., 2020) proposed an automated computer-aided diagnosis system for multi-class skin cancer classification using the HAM10000 dataset with seven classes. They conducted a comparative study analyzing the performance of five pretrained CNN models and four ensemble models. The results showed a maximum accuracy of 93.20% for individual models and 92.83% for ensemble models. However, high accuracy alone does not necessarily indicate the best model. The precision, recall, and f1-score values for all models in this study were below 90%, suggesting that improvements are needed to enhance the accuracy and overall classification performance.

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Another study by (Deif & Hammam, 2020) aimed to develop a more accurate computer-aided skin lesion detection system using the dilated convolution method in deep learning. They implemented dilated convolution on four different model architectures, VGG16, VGG19, MobileNet, and InceptionV3. The HAM10000 dataset with significant class imbalance, containing a total of 10,015 dermoscopy images from seven skin lesion classes, was used for training, validation, and testing. The best accuracies achieved in the dilated versions of VGG16, VGG19, MobileNet, and InceptionV3 were 87.42%, 85.02%, 88.22%, and 89.81%, respectively. Experiments to improve accuracy: parameter variation (epoch, learning rate, dropout), overcoming class imbalances (oversampling/undersampling), utilizing ResNet50 with standard convolution, and optimizing batch size and dropout regularization.

METHOD

Research Flow

The research flow involves several stages, including literature review, dataset collection, data preprocessing, CNN model training using MobileNet for feature extraction, classification using CNN and SVM, performance evaluation using evaluation metrics, result analysis, and conclusion. To gain a better understanding, please refer to **Fig. 1** below.

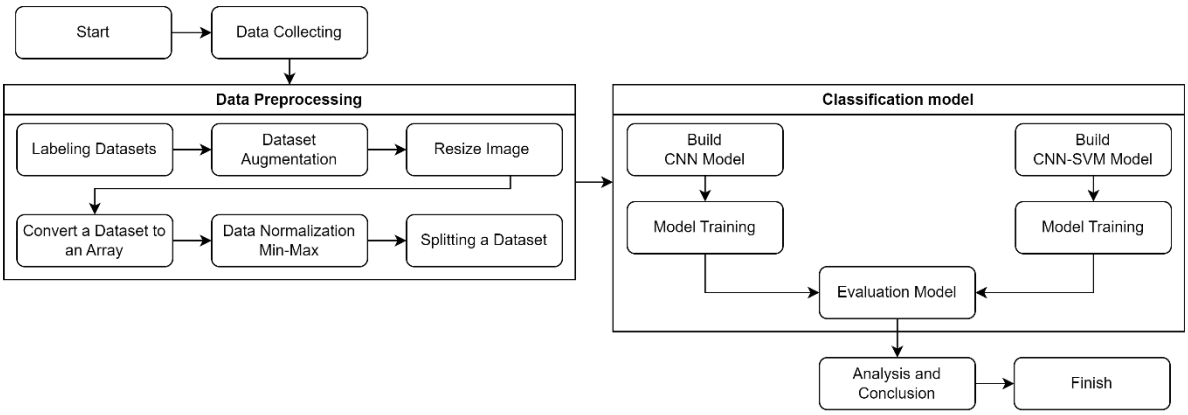

Fig. 1 Research Flow

Data Collection

The data used in this research is the HAM10000 dataset, which was downloaded from the Harvard Dataverse website. The HAM10000 dataset is a collection of 10,015 dermatoscopic images of 7 different types of skin diseases. An example of a sample image from the dataset can be seen in **Fig. 2** below.

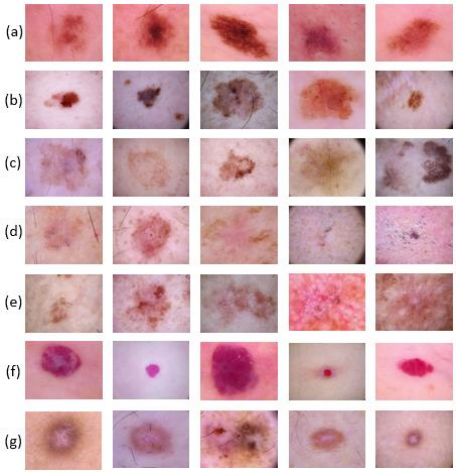

Fig. 2 Sample Dataset Image

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Fig 2 displays sample images of skin diseases from the HAM10000 dataset: (a) Melanocytic Nevi, (b) Melanoma, (c) Benign Keratosis-like Lesions, (d) Basal Cell Carcinoma, (e) Actinic Keratoses and Intraepithelial Carcinoma, (f) Vascular Lesions and (g) Dermatofibroma.

Data Preprocessing Stage

Dataset Labeling

In this stage, each image in the dataset is separated into folders with labels corresponding to the specific type of skin disease it represents. The results of the labeling process can be seen in Table 1.

Table 1. Labeling Datasets

No	Types of disease	Label Folder
1	Actinic Keratoses and Intraepithelial Carcinoma	akiec
2	Basal Cell Carcinoma	bcc
3	Benign Keratosis-like Lesions	bkl
4	Dermatofibroma	df
5	Melanocytic Nevi	nv
6	Melanoma	mel
7	Vascular Lesions	vasc

Data Augmentation

Data augmentation is performed to enhance the diversity of the dataset, prevent overfitting, and enrich the variations within the dataset to improve the model's quality. The augmentation techniques applied include rotation, shifting, flipping, zooming, and pixel filling. Examples of the augmentation techniques can be seen in **Fig 3**.

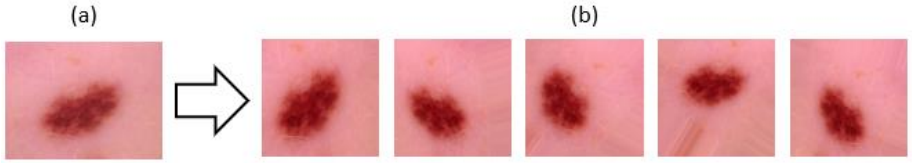

Fig. 3 Examples of image augmentation

In Figure 9.3 above, examples of augmentation applied to one of the dataset images are shown: (a) Image before augmentation (b) Image after augmentation. The number of datasets after the augmentation process can be seen in Table 2.

Table 2 Dataset After Prepocessing

No	Label	Number of Images
1	akiec	3000
2	bcc	3000
3	bkl	3000
4	df	3000
5	nv	3000
6	mel	3000
7	vasc	3000
Total		21000

Resizing Images

The collected dataset initially had images with a resolution of 600x450 pixels. However, to maintain consistency and align with the MobileNet architecture utilized, the images were resized to a uniform size of 224x224 pixels.

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Converting Dataset to Arrays, Data Normalization, Dataset Splitting

The image dataset is then converted into numerical arrays to be processed by the classification model. Additionally, data normalization is performed using the Min-Max method to ensure that pixel values fall within the same range and prevent dominance of specific features. Lastly, the dataset can be split into three parts: 80% for training, 10% for validation, and 10% for testing the classification model.

Training and Classification of the Model

After preprocessing the dataset, it is utilized in the training and classification processes to generate a model capable of recognizing and classifying different types of skin diseases. The training data (80%) is employed to train the model to effectively recognize patterns representing each disease type. The validation data (10%) is used to evaluate the model's performance during training. The testing data (10%) is employed to assess the final performance of the model after the training process concludes. The trained model is then applied to the unseen testing data, and the classification results are evaluated to measure the success rate of recognizing and classifying the skin diseases. Two models are constructed and utilized in this stage: the MobileNet architecture-based CNN model and the MobileNet architecture-based CNN-SVM model, as follows:

CNN Model

In the architecture of CNN, MobileNet comprises convolutional layers responsible for extracting features from the images. When skin lesion images are fed into the model, MobileNet's convolutional layers discern patterns and essential features within the images. Post feature extraction, MobileNet generates robust feature representations for each skin lesion image. These representations encapsulate significant image characteristics that can distinguish between different types of skin diseases.

The ultimate layers of MobileNet serve as the classification layers. They leverage the feature representations to categorize the skin lesion images into one of the seven designated types of skin diseases. Upon completion of the classification process, the MobileNet model generates predictions for each skin lesion image. The CNN-based classification process is depicted in Fig. 4.

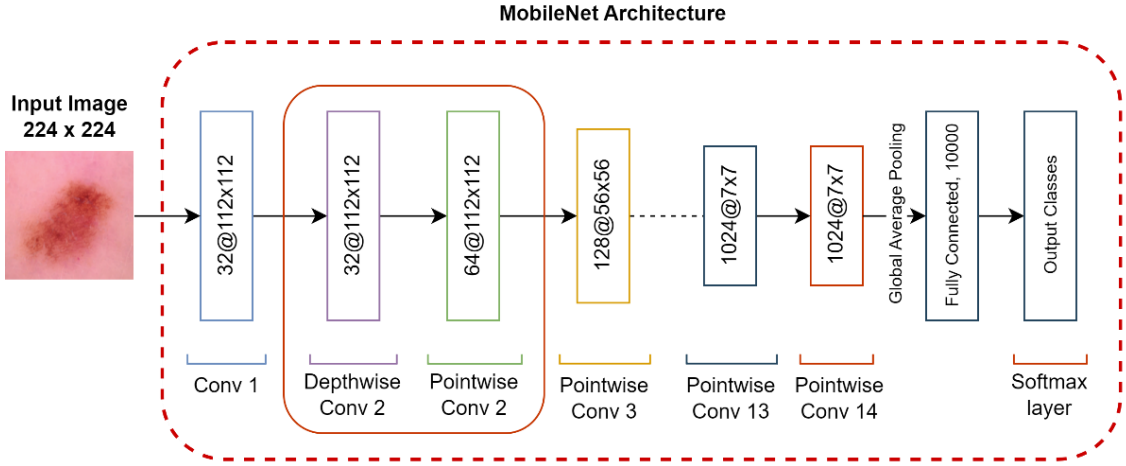

Fig. 4 CNN MobileNet Architecture

CNN-SVM Model

Similar to the CNN model, in the CNN-SVM model, CNN with the MobileNet architecture is used to perform feature extraction from skin lesion images. The CNN model consists of convolutional layers that can learn complex patterns at a deep pixel level. Each skin lesion image is fed into the CNN model, and the convolutional layers gradually extract important visual features from the images. This process generates more abstract feature representations that capture the unique characteristics of each type of skin disease.

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After feature extraction, we utilize a Support Vector Machine (SVM) model for classification. The training data features are used as input to train the SVM model. The SVM model learns the optimal decision boundary to differentiate between different classes, which are the 7 types of skin diseases in this case. The SVM model attempts to discover patterns in the training data that distinguish different skin diseases. For further details of the CNN-SVM model, refer to Fig. 5 below.

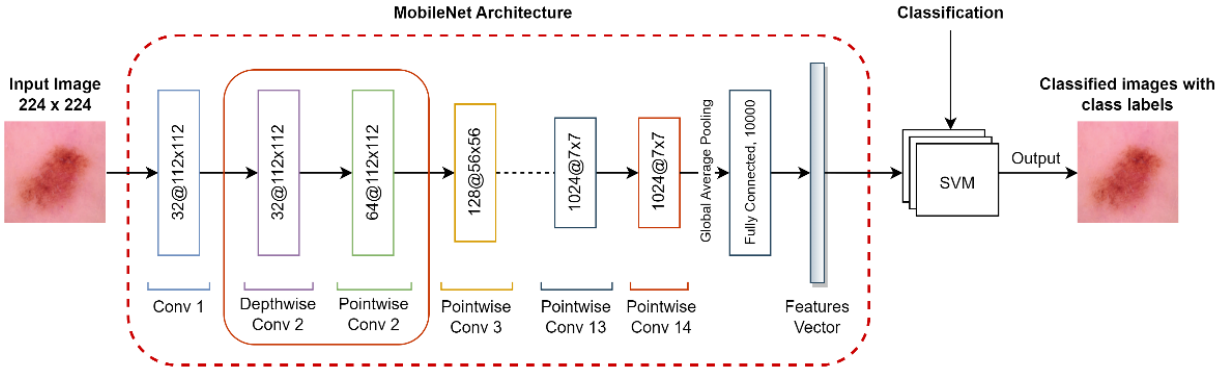

Fig. 5 CNN-SVM Model

Model Evaluation

After the classification process is completed, both the CNN model and the CNN-SVM model will generate predictions for each skin lesion image. These predictions will then be evaluated using performance metrics such as accuracy, precision, and recall. These metrics are crucial in assessing the model's performance in correctly classifying skin lesion images.

RESULT

This research compares two classification methods for classifying human skin diseases: Convolutional Neural Network (CNN) with MobileNet architecture and Convolutional Neural Network - Support Vector Machine (CNN-SVM) with several kernel types. The dataset consists of seven classes of skin diseases: akiec, bbc, bkl, df, mel, vasc, and nv, totaling 21,000 images.

Results of CNN Classification

The CNN model with MobileNet architecture demonstrates excellent performance in classification. After training with 80% training data, 10% validation data, and 10% testing data, the model achieves the highest training accuracy of 99% and validation accuracy of 93%. MobileNet architecture is run for 50 epochs with a batch size of 64, learning rate of 0.001, and SGD optimizer. Fig. 6 presents the training and validation accuracy and loss.

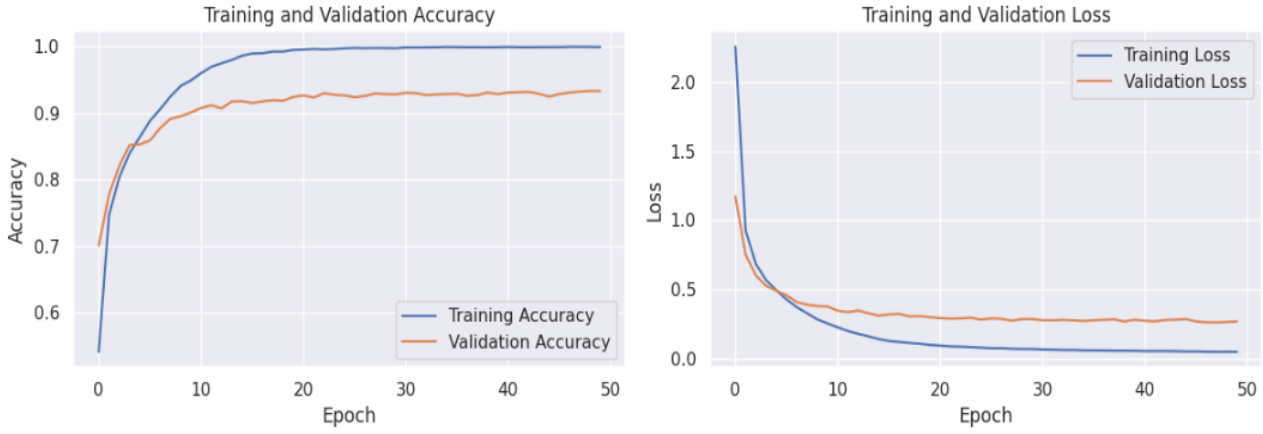

Fig. 6 Training and Validation Accuracy and Loss

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In the training and validation process shown in Fig. 6, the highest training and validation accuracies are 99% and 93%, and the lowest training and validation loss accuracies are 0.005 and 0.26, respectively. These results indicate that the CNN model can effectively recognize and understand complex patterns from the training data.

The CNN model achieves an accuracy of 93.47% in the testing phase, indicating its ability to generalize well to unseen data. The precision, recall, and F1-score values are also high in testing, at 93.55%, 93.74%, and 93.62%, respectively. This demonstrates the CNN model's accurate classification of various skin disease types and its capability to identify most of the actual skin disease cases. The classification results are presented in Table 3.

Table 3 Performance Metrics of CNN Classification

No	Metric	Value
1	Accuracy	93.47%
2	Precision	93.55%
3	Recall	93.74%
4	F1-Score	93.62%

The accuracy per class analysis shows good performance for almost all skin disease types, with the highest accuracy in classes df (Dermatofibroma) and nv (Melanocytic nevi), both reaching 100%. Although some classes have lower accuracy, such as akiec (94.44%), bbc (96.30%), and vasc (96.43%), overall, the CNN model successfully classifies skin disease types. The accuracy rates for each class can be seen in Table 4.

Table 4 Results of Disease Class Accuracy of CNN Model

No	Class	Accuracy
1	akiec	94.44%
2	bbc	96.30%
3	bkl	82.91%
4	df	100.00%
5	mel	86.10%
6	vasc	96.43%
7	nv	100.00%

Classification Results of CNN-SVM

The CNN-SVM model with various types of kernels, namely "poly," "rbf," "linear," and "sigmoid," was applied to a skin disease dataset using the CNN MobileNet architecture. The dataset was divided with a distribution ratio of 90% for training data and 10% for testing data. The results demonstrate a lower accuracy compared to the CNN model.

The testing of the CNN-SVM model using the "poly" kernel yielded a training accuracy of 90% and a testing accuracy of 81%. This model exhibited promising performance on both the training and testing data, though there is room for improvement to optimize its classification capabilities. An overview of the complete classification results can be seen in Table 5.

Table 5 Classification Results of CNN-SVM with Poly Kernel

No	Metric	Training	Testing
1	Accuracy	90%	81%
2	Precision	91%	80%
3	Recall	90%	80%
4	F1-Score	90%	80%

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The testing of CNN-SVM with the "RBF" kernel resulted in a training accuracy of 86% and a testing accuracy of 79%, as shown in Table 6. This indicates that the model performs well in classifying the training data, but its generalization ability is less effective when applied to the testing data.

Table 6 Classification Results of CNN-SVM with RBF Kernel

No	Metric	Training	Testing
1	Accuracy	86%	79%
2	Precision	86%	78%
3	Recall	86%	78%
4	F1-Score	85%	78%

The testing of CNN-SVM with the "linear" kernel revealed a training accuracy of 93% and a testing accuracy of 72%. These outcomes indicate that the model exhibits proficiency in classifying the training data, yet it struggles to generalize effectively to the testing data, as presented in Table 7.

Table 7 Classification Results of CNN-SVM with Linier Kernel

No	Metric	Training	Testing
1	Accuracy	92%	72%
2	Precision	92%	72%
3	Recall	92%	71%
4	F1-Score	92%	71%

The testing of CNN-SVM with the "sigmoid" kernel yielded a training accuracy of 52% and a testing accuracy of 51%, as displayed in Table 8. These findings indicate that the model is encountering overfitting issues, whereby the strong performance on the training data does not translate to equally good performance on the testing data.

Table 8 Classification Results of CNN-SVM with Sigmoid Kernel

No	Metric	Training	Testing
1	Accuracy	52%	51%
2	Precision	51%	51%
3	Recall	52%	51%
4	F1-Score	51%	50%

Overall, the CNN-SVM model's performance remains inferior compared to the CNN model. Enhancing the performance of the CNN-SVM model could involve parameter adjustments and further exploration of kernels.

The accuracy testing results per class from the CNN-SVM model indicate that certain classes, such as "bkl" and "mel," also encounter challenges in accurate classification by this model. The accuracy for classes "bkl" and "mel" across all kernels falls below 60%, revealing SVM's difficulty in precisely identifying these types of skin diseases.

Table 9 Results of Disease Class Accuracy of CNN-SVM Model

No	Class	Kernel Poly	Kernel RBF	Kernel Linear	Kernel Sigmoid
1	akiec	82.29%	80.90%	72.92%	61.11%
2	bbc	84.78%	83.23%	73.91%	40.68%
3	**bkl**	**57.86%**	**52.51%**	**48.49%**	**22.07%**
4	df	89.14%	86.58%	79.87%	49.52%
5	**mel**	**59.22%**	**56.38%**	**48.94%**	**32.98%**
6	nv	91.19%	91.53%	80.68%	73.56%
7	vasc	98.01%	97.34%	94.02%	76.08%

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Table 9 above shows the results of disease class accuracy from the CNN-SVM model with all kernels, showing that the performance of this model also varies. Some classes such as "vasc" and "df" have relatively high accuracy across all kernels, but the "bkl" and "mel" classes consistently show lower accuracy across all kernels. This suggests that the CNN-SVM model needs to be improved to achieve better classification results.

DISCUSSIONS

The excellent performance of MobileNet's CNN architecture model captures complex patterns in data effectively. The high accuracy and balance of precision-recall values indicate that this model is able to accurately classify various types of skin diseases. Conversely, CNN-SVM models with different kernel types show varying performance. "poly", "rbf" and "linear" kernels produce better results because they are able to separate data into more separate classes. However, the "sigmoid" kernel has limitations in capturing complex patterns, resulting in lower accuracy and F1-score.

A comparison between the CNN and CNN-SVM models shows that the CNN model is consistently superior compared to the CNN-SVM model with various kernel types. The CNN model's ability to generalize to never-before-seen test data and its ability to recognize complex patterns make it a better choice for classification of skin disease types.

The use of the CNN-SVM model with a specific kernel can be an alternative option if the right parameter adjustments are made. However, overall, the CNN model with MobileNet architecture remains the superior choice in the classification of types of human skin diseases. These findings highlight SVM's challenges in handling datasets with overlapping features and the importance of selecting the right kernel to achieve optimal performance.

The limitation of the CNN-SVM Model in this study is sensitivity to overlapping data. When there are classes of skin diseases that have similar or overlapping features, the CNN-SVM model has difficulty distinguishing between these classes. If similar feature patterns are found across multiple classes, the model will find it difficult to decide on the right classification.

The comparison between CNN and CNN-SVM models provides valuable insights for future research in medical image analysis and skin disease classification. Researchers can explore different types of kernels and techniques to improve the performance of CNN-SVM models, as well as overcome the challenges of overlapping classes and complex feature representations.

CONCLUSION

Based on the results of this study, it can be concluded that the CNN model with MobileNet architecture is a better choice for classification of human skin disease types compared to the CNN-SVM model with "poly," "rbf," "linear," and "sigmoid" kernels. The CNN model is able to achieve high accuracy and has a good balance in recognizing different classes of skin diseases. The test accuracy results that reached 93.47% show the ability of the CNN model to classify images well.

The results of this study contributed to the development of image classification models for the diagnosis of skin diseases, and provided insight into the selection of appropriate models for specific classification tasks. Although the CNN-SVM model with a "poly" kernel also performed well in training accuracy, its ability to classify images on test data still needs to be improved. For the use of CNN-SVM models with "rbf", "linear", and "sigmoid" kernels, further research is needed to improve performance in low-accuracy classes and optimize more precise parameter selection. Comparison of test results shows that the CNN-SVM model has lower performance compared to the CNN model. The CNN-SVM model has lower accuracy, precision, recall, and F1-score, especially in "sigmoid" kernels. Despite this, the "poly" and "rbf" kernels showed better performance, but still lost when compared to the CNN model.

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