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Comparison of CNN and SVM Methods on Web-based Skin Disease Classification Process

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Abstract: Skin, as the outermost layer of the body, is often in contact with bacteria, germs and viruses because of its most external position. Skin illness is the third most common ailment seen in outpatient settings across the country's hospitals. Therefore, maintaining healthy skin is important because it protects the body's internal organs from injury and attack by pathogens. The development of image classification, such as the classification of skin diseases, has become a focus in the health sector. This research analyses the performance of Convolutional Neural Network (CNN) and Support Vector Machine (SVM) in web-based skin disease classification and overcomes the problem of imbalanced training data. With data augmentation and preprocess, this research improves data generalization and compares performance metrics such as Recall, Accuracy, and F1 Score. The results show that the average accuracy of CNN is 83.8%, while SVM reaches 81%. Although both models have high metrics for the normal class, other more complicated classes can only be handled by CNN with a value of more than 0.9. Apart from that, the CNN method also provides a higher Confidence Score than SVM, as well as a faster execution time. In conclusion, the CNN method is superior and recommended for skin disease classification based on web applications based on various performance test results.

Keywords: Classification**,** Convolutional Neural Network, Image**,** Support Vector Machine, Web Application

INTRODUCTION

Skin illness is the third most common ailment seen in outpatient settings across the country's hospitals. It is one of the diseases that often affect Indonesians. One study compared CNN models (Inception V3: 72%, MobileNet v1: 58%) for dermoscopic image classification(Purnama et al., 2019). In 2022, another study used CNN to classify skin diseases with 81.75% accuracy using 3000 color images but needed more data and fine-tuning(Saifan & Jubair, 2022). An ensemble method reached 98.64% accuracy(Verma et al., 2019). In recent research, the "medilab-plus" web-based skin disease detection system using CNNs achieved high accuracies (88%, 85%, 84.7%) for identifying various skin conditions(Akyeramfo-Sam et al., 2019). It provides rapid results in 0.0001 seconds, aiding quick diagnoses and offering real-time learning opportunities for Ghana's medical students. Another study on Psoriasis using CNN reached 82.9% accuracy for Plaque Psoriasis and 72.4% for Guttate Psoriasis(Roslan et al., 2020). AI matched dermatologists in classifying benign nevi and melanoma images, outperforming in sensitivity and specificity(Brinker, Hekler, Enk, Berking, et al., 2019).

A recent study introduced a novel HSIC framework with a simplified 2D-3DCNN architecture, improving feature extraction and classification accuracy (Yu et al., 2020). Another study analyzed colon cell images with CNN models, including MobileNetV2, achieving an impressive 99.67% accuracy(Tasnim et al., 2021). In 2023, research evaluated ten pretrained models for hyperpigmented skin diagnosis, with MobileNet showing potential for clinical applications (Lu et al., 2023). In a 2023 study, two methods achieved over 99% accuracy in classifying benign or malignant skin tumors(Magdy et al., 2023). In 2019, various CNN algorithms reached recalls of up to 92.9%, 89.2%, and 84.3% for specific facial skin conditions after transfer learning(Wu et al., 2019). A 2020 meta-analysis favored Random Forest and Support Vector Machines in remote sensing, especially for land use and land cover applications(Sheykhmousa et al., 2020). Machine learning, especially CNNs, showed potential for skin disease diagnosis and prevention(Bhadula et al., 2019).

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In an effort to address the difficulty of separating crack and non-crack regions in raw images frequently impacted by irregular noise, practical preprocessing techniques were introduced in a recent study to improve the training efficiency of deep learning models designed for road surface crack detection from image data(Shin et al., 2020). Another study used the Support Vector Machine (SVM) algorithm to classify skin disease samples and achieved an impressive classification accuracy of about 90%. The study focused on the early detection and differentiation of skin diseases, specifically Melanoma. Additional training data and different kernels could potentially lead to even greater improvement, according to the study(Kumar et al., 2019). Furthermore, a groundbreaking study demonstrated how a deep-learning algorithm trained with publicly available dermoscopic images performed in comparison to dermatologists, emphasizing the algorithm's potential to support clinical melanoma detection(Brinker, Hekler, Enk, Klode, et al., 2019).In 2019, a method based on image processing was proposed to address the need for effective skin disease detection in areas where skin diseases are common. This method achieved an impressive 100% accuracy rate in detecting three different types of skin diseases(Alkolifi Alenezi, 2019).

Utilizing SVM, a proposed skin cancer detection system achieved 95% accuracy, providing a painless and efficient alternative to biopsy, ensuring prompt and accurate diagnosis for early intervention and increased patient benefit (Thakur & Panwar, 2023). Another recent studies demonstrates the effectiveness of SVM in soybean disease classification, achieving a classification accuracy of 94.1435%, outperforming the Deep Learning classifier with an accuracy of 88.7262% (Thaiyalnayaki & Joseph, 2021). Another study employing a Support Vector Machine (SVM) with radial basis function kernel to achieve 94.87% accuracy in fast and painless skin cancer detection, particularly focusing on distinguishing melanoma from non-melanoma. Another recent studies showcases an advanced support vector machine (SVM) classifier with feature engineering, achieving a remarkable 99.12% accuracy in breast cancer classification, emphasizing the potential for machine learning, particularly SVM (de Melo & Davtyan, 2023). All of these studies highlight how important sophisticated computational methods are for correctly classifying and identifying skin diseases.This information can be used to inform future research and improve patient care.

The testing phase of this study is pivotal for evaluating the performance of CNNs and SVMs in the context of skin disease classification. Rigorous testing procedures will be employed to assess the accuracy, precision, recall, and F1 score of each algorithm. To test how each model performs classification in web-application, execution time was measured for each model. Testing on this metric is carried out by repeatedly do claassification utilizing the web-application.

Classifying skin diseases is crucial in dermatology for accurate diagnosis and treatment planning. An effective system helps dermatologists identify specific diseases based on visual symptoms. Comparing classification algorithms like Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) is essential to inform method selection for skin disease classification. Previous research supports CNNs and SVMs as reliable, with over 80% accuracy. This nuanced comparison reveals algorithmic strengths and weaknesses, guiding practitioners in choosing the optimal approach. The study aims to diagnose skin disorders early by comparing CNN and SVM methods in a web application for skin disease identification, addressing challenges such as imbalanced datasets and varying research outcomes. It contributes to better understanding effective ways to categorize skin conditions.

METHOD

Development of the Model

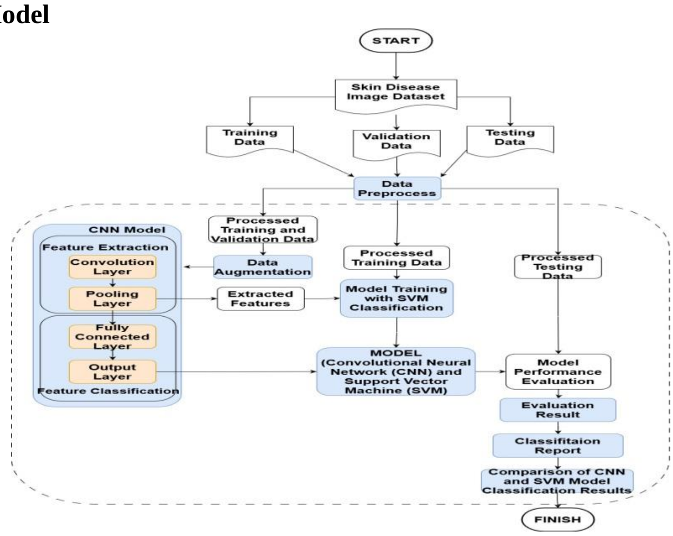

Fig. 1 Research and Model Development Flow

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Data preprocessing is a crucial step in developing deep learning models for image datasets. It involves tasks like turning images into grayscale, reducing noise, and enhancing contrast to improve image quality and highlight important features. Data augmentation further diversifies the dataset by making random changes to training images, like rotation and pixel adjustments. Additionally, data preprocessing can include dataset splitting, batch size selection, and handling empty pixels to prepare the data for effective learning. A well-preprocessed dataset helps the model classify images accurately and understand dataset variations. The Convolutional Neural Network (CNN) used in this architecture is optimized for image classification. It uses convolution layers with 3x3 filters and ReLU activation for feature extraction, followed by max-pooling to reduce data dimensionality. This process is repeated to enhance image representation. A flatten layer converts the 2D matrix to a 1D vector before classification using a Dense layer. Dropout is used to prevent overfitting. The output layer employs softmax activation for five-class classification. The Support Vector Machine (SVM) model classifies features extracted from the CNN model. These features are extracted at the last pooling layer, allowing SVM to classify based on these representations all model development process presented in Fig. 1.

Data Collection and Pre-processing

AS Shown in Fig. 2. Images/pictures of skin diseases from Kaggle and direct sample collection make up the dataset; the labels for eczema and melanoma are from Dermnetz and the International Skin Image Collection; the data for the Normal label is gathered from the collection of skin samples from Indonesia. I use 500 images from each of the five labels I used for the dataset "Eczema, Melanoma, Atopic Dermatitis, Basal Cell Carcinoma (BCC), and Normal" to test the performance of the model. Training and testing data are compared at a ratio of 9:1, 8:2, 7:3, and 6:4.

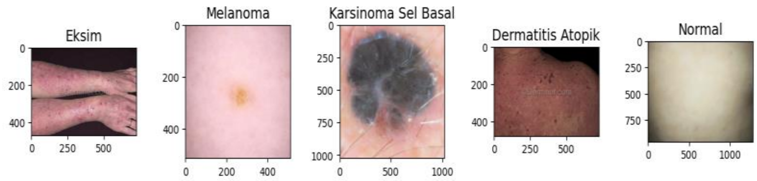

Fig. 2 Data Sample

Data preprocessing, a vital step in building deep learning models, is especially important when working with image datasets. This process involves preparing the data to meet the model's requirements and ensuring its quality. Effective data preprocessing is essential for training models to accurately recognize and classify images, such as in the case of skin disease recognition. It forms the foundation for achieving good results in various deep learning applications.

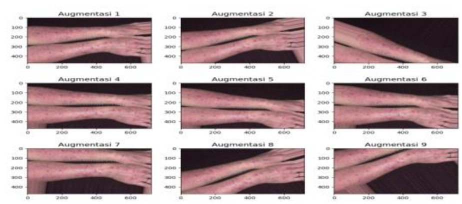

Fig. 3 Augmentation in Images

Data augmentation is one of the primary components of picture data preparation. To add more variance to the dataset, data augmentation entails transforming training photos randomly. This improves the model's ability to identify patterns and features in a broad range of images. Zoom, tilt, pan, and rotation are a some of the transformations that have been used. In addition, as shown in Fig. 3, pixel intensity normalization is also implemented by modifying the pixel value range to fall between 0 and 1.

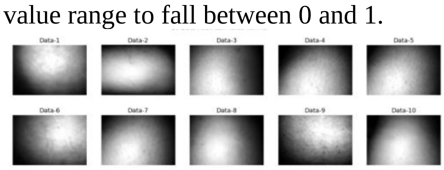

Fig. 4 Image of Pre-processed Results on Dataset

A number of processes are involved in the preprocessing process to get a picture ready for additional analysis. The cv2 library is used to first convert the image to grayscale, which reduces the image to a single channel and facilitates processing. Gaussian Blur, a method that smoothes an image by averaging pixel values within a specified kernel size here set at (5, 5) is then used to eliminate noise from the grayscale image. Histogram Equalization is the last technique used to provide contrast enhancement. It redistributes the intensity values throughout the picture to increase visibility and feature identification in the processed image. The example of pre-processed image shown in Fig.4.

Web Application Development

This website was built using several programming languages such as HTML Bootstrap 5, CSS and Python. The following is a display of the website that developed:

Front Page Interface:

Fig. 5 Image front PageInterface

In the front page of the web application users can access the home page , article page and login or signup to proceed classifying image.

Classification Page Interface:

Fig. 6 Image of Classification Page Interface

in classification page users can upload image to start the classification of skin desease and get the result in classification result page as shown in Fig. 6. ClassificationHistory page used by user to see their classification history results.

Performance Evaluation

Various metrics, such as F1-score, accuracy, precision, and recall, assess image classification performance, with F1-score providing a balanced measure of accuracy in object detection. Execution time and prediction confidence are considered in online tests and precision and recall offer insights into the model's effectiveness in avoiding specific mistakes.

Recall (Sensitivity or True Positive Rate)

Recall (Sensitivity or True Positive Rate) measures the extent to which the model is able to identify all true positive samples.In mathematical notation, recall is calculated using the following formula:

$$R = \frac{TP}{(TP+FN)} \quad (1)$$

When,The term TP (True Positive) refers to the percentage of accurate predictions. False Negative, or FN, is the number of false negative predictions.

Precision

In mathematical notation, precision is calculated using the following formula:

$$Precision = \frac{TP}{(TP+FP)} \quad (2)$$

When, The term TP (True Positive) refers to the percentage of accurate predictions.False Positive (FP) refers to the amount of negative samples that were incorrectly classified as positive or false positive predictions. Precision is a classification-related evaluation metric that quantifies how well a model can accurately identify positive samples. It gauges the proportion of the model's optimistic forecasts that are genuinely positive or accurate.

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Accuracy

This is a simple and easy-to-understand metric that calculates the total percentage of correct predictions compared to the overall evaluated sample.

In mathematical notation, accuracy is calculated using the following formula:

$$Accuration = \frac{TP + TN}{(TP + TN + FP + FN)} \quad (3)$$

Where: TP (True Positive) is the number of truly positive predictions. TN (True Negative) is the number of truly negative predictions. The quantity of false positive predictions, or negative samples mistakenly identified as positive, is known as FP (False Positive). The quantity of negative false predictions, or positive samples incorrectly identified as negative, is known as FN (False Negative).

F1-Score

An assessment metric called the F1-Score is used in classification to gauge how well recall and precision are balanced. The harmonic mean of recall and precision is the F1-Score. This assigns equal weight to both, which is highly helpful in preventing imbalances that could arise from using only accuracy. F1-Score values of 0 denote extremely poor performance, while values of 1 denote flawless performance.

F1-Score is calculated using the following formula:

$$F1 - Score = 2 \times \frac{(Precision \times Recall)}{(Precision + Recall)} \quad (4)$$

In the formula above, precision is a metric that assesses how accurate the model's optimistic predictions are. A metric called recall assesses how well the model can identify all real positive samples.

Confusion Matrix

The degree to which the classification model can accurately or inaccurately classify the data is indicated in this matrix. There are typically four primary components that comprise the confusion matrix:

		Predicted	
		Negative (N)	Positive(P)
Actual	Negative(N)	True Negative (TN)	False Positive (FP)
	Positive(P)	False Negative (FN)	True Positive (TP)

Fig. 7 Confusion Matrix

In Fig.7, True Positive (TP) and True Negative (TN) represent correct classifications, while False Positive (FP) and False Negative (FN) indicate instances of incorrect positive and negative classifications, respectively.

RESULT

Model Development Results

To test the performance of the two methods, there are 4 models built with different amounts of training and testing data. The following table shows how the data and model names are divided:

Table 1
Model Development

Model Name	Training Data	Test Data	Accuracy (%)
CNN1	450	50	84,4
SVM1	450	50	80,0
CNN2	400	100	85,0
SVM2	400	100	83,0
CNN3	350	150	84,0
SVM3	350	150	80,0
CNN4	300	200	81,0
SVM4	300	200	80,3

All CNN models were trained over 50 epochs using the "Adam" optimizer. and the Support Vector Classification (SVC) component of the Scikit-Learn (sklearn) library was used to train the SVM model using the SVM algorithm and a "Linear" kernel. The quantity of training data affects the accuracy value of the model, albeit not significantly.

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Model Performance Evaluation

In image classification, we use F1-score, accuracy, precision, and recall to see how well the model works. F1-score combines precision and recall, helping us understand how the model balances false alarms and misses. When testing online, we also check how quickly the model works and its confidence in predictions.

Precision and Recall

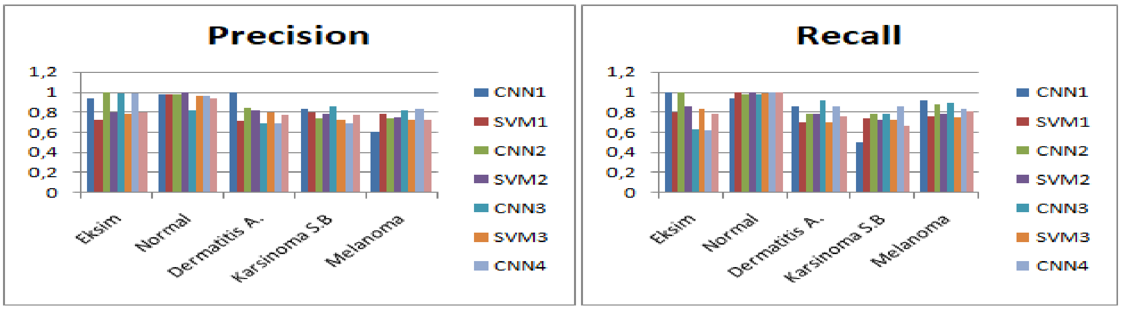

Fig. 8 Graph of Precision and Recall Value

Classes including atopic dermatitis, normal, and eczema have values greater than 0.9. Accuracy data for each class are shown in Fig. 8, which indicates that the normal class and the CNN method have good average precision values. The normal and eczema classes also have high recall values in the recall data, with the CNN method and the normal class having good average recall values.

F1 Score

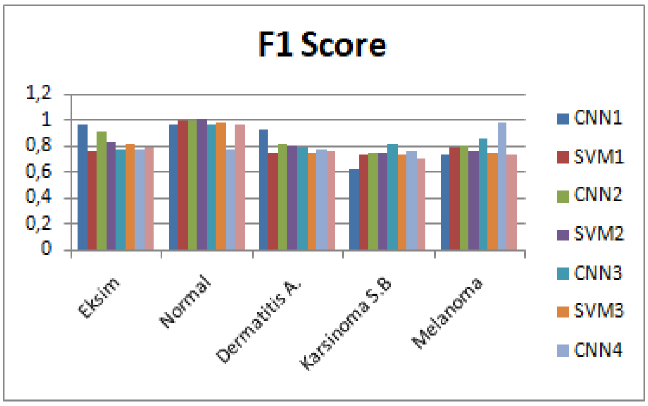

Fig. 9 F1-score Graph

Fig. 9 provides a visualization of the F1 Score value data generated by each classification model for each label or class where classes with a high value of more than 0.9 are in the eczema, normal, and melanoma classes. The data also shows that the Normal class and CNN method have good average F1 Score values in general.

Confusion Matrix

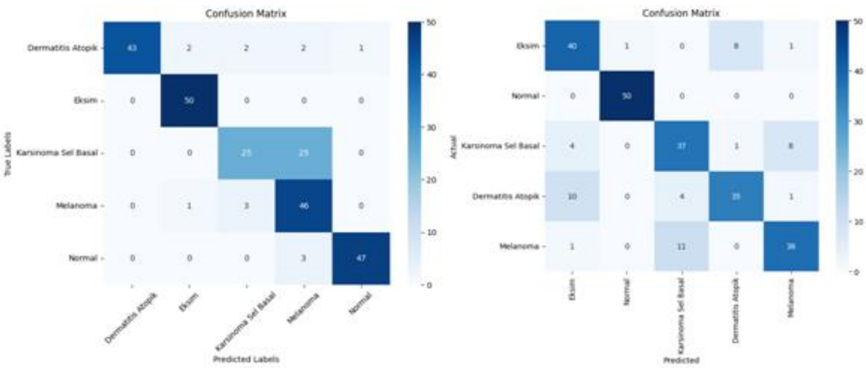

Fig. 10 Confusion Matrix of CNN1 and SVM1 Model

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The Confusion Matrix in Fig. 10 illustrates how the CNN1 model successfully classifies correctly (True Predictions) as much as 211 test data while the SVM1 model in Fig.18 successfully classifies correctly as much as 200 test data.

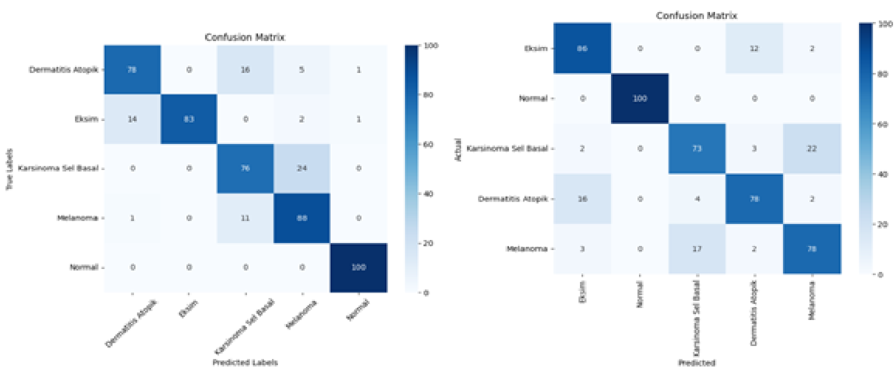

Fig. 11 Confusion Matrix of CNN2 and SVM2 Model

The Confusion Matrix in Fig. 11 illustrates how the CNN2 model successfully classifies correctly (True Predictions) as much as 425 test data while the SVM2 successfully classifies correctly as much as 415 test data.

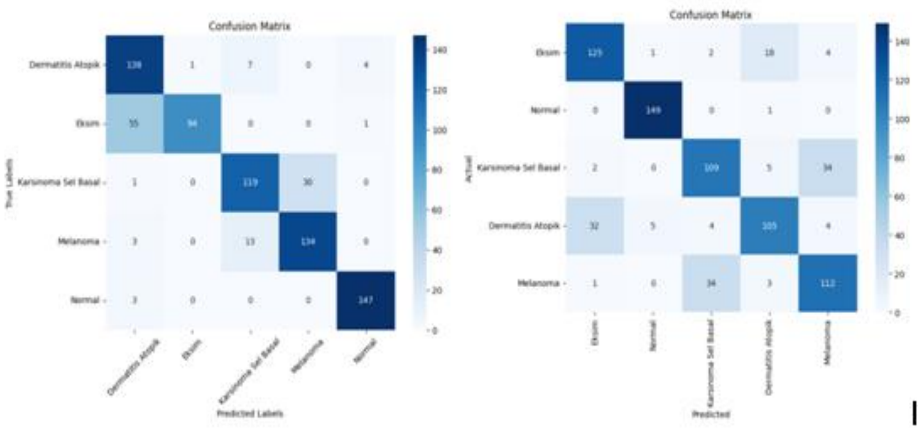

Fig. 12 Confusion Matrix of CNN3 and SVM3 Model

Confusion Matrix in Fig. 12 illustrates how the CNN3 model successfully classifies correctly (True Predictions) as much as 632 test data while the SVM3 managed to correctly classify as much as 600 test data.

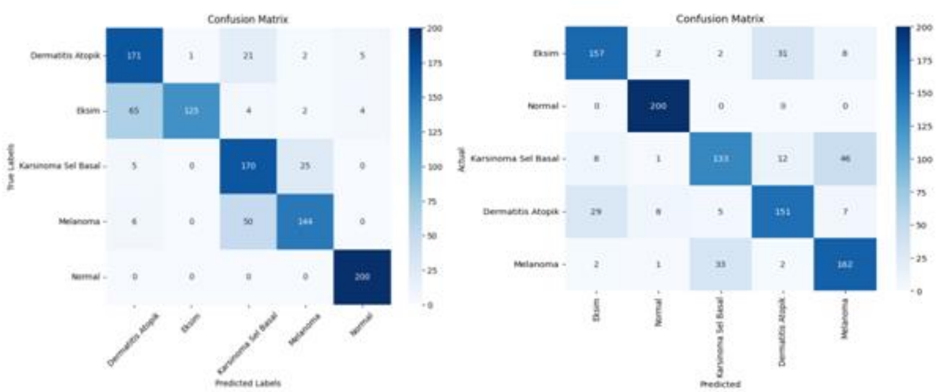

Fig. 13 Confusion Matrix of CNN4 and SVM4 Model

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In Fig. 13, the Confusion Matrix shows CNN4 and SVM4 correctly classify 810 and 803 test data, respectively. Both models excel in predicting the normal class due to its simpler features, resulting in accurate classification.

Performance Evaluation of Classification Process in Web Applications

Table 2
Performance Evaluation Table of Classification Process with Web

Models	Iteration	Confidence Score CNN (%)	Confidence Score SVM (%)	Execution Time CNN (seconds)	Execution Time SVM (seconds)
1	1	100	76,01881623	0,2587416172	0,4709537029
1	2	99,99998808	69,84345317	0,1831264496	0,2675602436
1	3	100	69,32560205	0,1923940182	0,2624030113
1	4	100	73,32479954	0,1838684082	0,2599122524
1	5	87,70428896	65,76693654	0,2372260094	0,3033061028
1	6	56,69609904	65,5997932	0,2830657959	0,3824923038
1	7	89,00547028	75,32106638	0,1679401398	0,3218412399
1	8	99,57267046	67,64032245	0,1569504738	0,2150557041
1	9	99,76219535	67,12873578	0,1899857521	0,2159347534
1	10	99,10929799	66,98091626	0,1932559013	0,2492947578
2	11	100	74,86031651	0,2679941654	0,4044489861
2	12	100	68,82408857	0,2015709877	0,251449585
2	13	100	65,20428061	0,2267684937	0,2831470966
2	14	100	68,27479601	0,1903984547	0,2432844639
2	15	72,01032639	66,52262807	0,2314915657	0,3201520443
2	16	72,01032639	66,52262807	0,3178200722	0,4454262257
2	17	95,81017494	67,27556586	0,1546592712	0,217240572
2	18	82,29590058	65,10429382	0,1700921059	0,2141366005
2	19	99,99409914	67,69435406	0,1633999348	0,2200336456
2	20	99,99090433	67,55847931	0,2507283688	0,3757970333
3	21	99,99558926	67,35637784	0,2176177502	0,2307798862
3	22	99,9782145	69,41133142	0,1268861294	0,1775510311
3	23	100	76,17630363	0,1768295765	0,23427248
3	24	100	73,60847592	0,2242007256	0,3168356419
3	25	72,67973423	65,57841897	0,2707931995	0,2635324001
3	26	72,30121493	64,54417109	0,3762743473	0,4271659851
3	27	87,70906329	73,32233191	0,1495962143	0,2073206902
3	28	98,61816168	65,20665288	0,2054741383	0,3122506142
3	29	99,98879433	66,29667282	0,2474431992	0,3015844822
3	30	99,98372793	66,1794126	0,1816909313	0,2179393768
4	31	93,22323799	66,15669727	0,2360084057	0,2344095707
4	32	99,99585152	68,31178665	0,125877142	0,1592383385
4	33	100	67,32859015	0,2254657745	0,3688616753
4	34	100	67,72461534	0,2292556763	0,3899846077
4	35	56,15991354	38,18165362	0,2703704834	0,2585430145
4	36	59,54729319	64,12062049	0,2497251034	0,3072133064
4	37	99,78601336	65,98832607	0,1667449474	0,2028508186
4	38	52,02479959	65,08923769	0,1555461884	0,1953918934
4	39	99,99980927	66,62905216	0,1811034679	0,1992139816
4	40	99,99972582	66,74998999	0,2065520287	0,2079000473

The process of testing the performance of the classification process using web applications is carried out using the execution time metrics and the confidence level generated by the model. Table 2 shows the results of testing 40 iterations and 10 iterations on each CNN and SVM model with the comparison in table 1.

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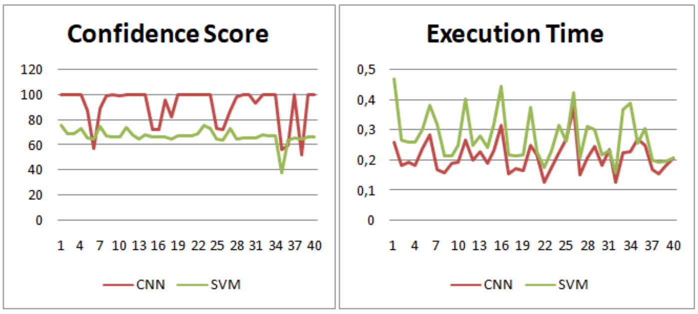

Fig. 14 Graph of Confidence Score and Execution Time Testing Results

Fig. 14 shows how the confidence score and Execution Time generated by the CNN and SVM models compares. Based on the results shown CNN is overall superior in predicting classification results even though there are several times it has a lower value compared to SVM. Based on the data, the execution time of the SVM model tends to be longer than the classification with CNN, the difference from the execution time of the classification model can reach more than 0.1 seconds, which looks quite significant after being visualized.

DISCUSSIONS

The development of the model involves a comprehensive process, as depicted in Fig. 1. The Convolutional Neural Network (CNN) architecture, optimized for image classification, employs various techniques such as data preprocessing, data augmentation, and Support Vector Machine (SVM) classification to enhance its accuracy. The model development results, as outlined in Table 1, provide insights into the performance of different models based on varying amounts of training and testing data. The quality of the dataset is crucial for effective model training. The combination of images from Kaggle, Dermnetz, the International Skin Image Collection, and skin samples from Indonesia forms a diverse dataset for skin disease classification. The importance of data preprocessing is highlighted, involving tasks such as grayscale conversion, noise reduction, contrast enhancement, and pixel normalization. The processed images, as illustrated in Fig. 4, demonstrate the effectiveness of these techniques in preparing the dataset for analysis.

The integration of the developed model into a web application, presented in Figs. 5 and 6, expands its usability and accessibility. The front page interface allows users to navigate through the application, access articles, and log in for image classification. The classification page interface enables users to upload images and receive results, enhancing the practicality of the model for real-world applications. The performance of the model is thoroughly assessed using various metrics, including F1-score, accuracy, precision, and recall. The confusion matrix, as depicted in Figs. 10-13, provides a detailed breakdown of the model's ability to correctly classify different skin conditions. The results show promising accuracy values for both CNN and SVM models across different training data sizes.

Table 1 illustrates the performance of CNN and SVM models across different training data sizes. Based on the research carried out, the average accuracy obtained for 4 CNN models was 83.8%, while for 4 SVM models the average accuracy was 81%, these results show a competitive result. Because the normal class has simpler features than other more complicated classes, only CNN is able to achieve a value of more than 0.9 in these metrics. In contrast, the recall, precision, and F1 score metrics of the normal class have quite high values for both CNN and SVM models. The impact of training data size on accuracy is noticeable, emphasizing the importance of dataset quality and quantity in model development. Table 2 presents the performance evaluation of the classification process in web applications. The comparison of confidence scores and execution times between CNN and SVM models, as shown in Fig. 14, highlights the efficiency of CNN in predicting classification results. The observed longer execution times for SVM underline the computational advantages of CNN in this context.

The research findings contribute novel insights into the development of an optimized CNN model for skin disease classification. The integration of effective preprocessing techniques, diverse dataset sources, web application deployment, and a thorough performance evaluation positions the study at the forefront of advancements in the application of deep learning to dermatology. These findings collectively enhance the understanding of the model's capabilities and its potential impact on addressing challenges in skin disease diagnosis and classification.

CONCLUSION

Based on the research carried out, the average accuracy obtained for 4 CNN models was 83.8%, while for 4 SVM models the average accuracy was 81%. Because the normal class has simpler features than other more complicated classes, only CNN is able to achieve a value of more than 0.9 in these metrics. In contrast, the recall, precision, and F1 score metrics of the normal class have quite high values for both CNN and SVM models. The

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average value of confidence score obtained by the model using the CNN method is 91.1%, while for the SVM method it is only 67.5%. The average execution time obtained using the CNN method is 0.21 seconds while using the SVM method is 0.27 seconds. It can be concluded that the CNN method is superior and it is recommended to be able to carry out a web application-based classification process based on the results of various test metrics. Future research efforts may include refining CNN architectures to increase their efficacy, investigating ensemble techniques that combine CNN and SVM models to increase precision, and creating real-time applications to address execution time efficiency issues. These efforts will ultimately advance the potential of web-based classification procedures in the skin disease classification domain.

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