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Image Processing in Classifying Dermatological Diseases

submitted by the author

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Submitted on: date

**Affirmation in lieu of an oath**

I assure that I have written the above work independently and have not used any other aids for this purpose than those indicated. All passages of the work that have been taken literally or analogously from external sources are marked as such.

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# Abstract

The purpose of this paper is to research the utilization of image processing techniques to classify dermatological diseases. This study tries to find an efficient model to categorize various skin diseases based on dermoscopic images of skin lesions. For this reason, a dataset with more than 1000 images and eight different classes was used. The models that were developed and compared are SVM and Random Forest Classifier. Since SVM had a slightly higher accuracy than Random Forest Classifier, it was used to create an interactive prompt for the user to see how well the system performs. The findings contribute to the understanding of the effectiveness of computer-based systems in dermatology.

**Keywords**

Image processing, skin diseases, dermatological disease classification, skin lesions, neural networks.

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1. **PART ONE: RESEARCH**

# Research Question and Task

The research questions for this task are:

1. Why is the classification of skin diseases important in dermatology?
2. How is the process of classifying dermatological diseases carried out?
3. What is the best way to categorize skin diseases?

Table 1: Field of research and research question specified by the PICOC method

|  |  |
| --- | --- |
| Population | Skin lesions |
| Intervention | Skin disease classification using SVM and Random Forest Classifier |
| Comparison | SVM vs Random Forest Classifier |
| Outcomes | Highly accurate prediction of skin diseases based on dermoscopic images |
| Context | Dermatology |

# Methodology

## Studies Selection Strategy

This paper collects the information from different articles and research papers to review the detection of bird sounds in the environment. The articles selected for this study were enlisted in the Google Scholar database.

Table 2: The study selection strategy conducted on Google Scholar database

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Database:  Google Scholar | Search words | Filters | Number of records | Date of search |
| #1 | classifying |  |  |  |
| #2 | skin disease |  |  |  |
| #3 | image processing |  |  |  |
| #4 | #1 AND #2 AND #3 | Studies published between 2015-2024 | 18100 | 18.11.2024 |

Table 3: The study selection strategy conducted on Google Scholar database

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Database:  Google Scholar | Search words | Filters | Number of records | Date of search |
| #1 | classifying |  |  |  |
| #2 | skin disease |  |  |  |
| #3 | dermatological disease |  |  |  |
| #4 | image processing |  |  |  |
| #5 | #1 AND #2 OR #3 AND #4 | Studies published between 2015-2024 | 18700 | 19.11.2024 |

Records identified through database searching (n = 19)

Additional records identified through other sources (n = 2)

Records after duplicates removed (n = 21)

Records screened (n = 21)

Records excluded (n = 6)

Full-text articles assessed for eligibility (n = 15)

Studies included in qualitative synthesis (n = 0)

Studies included in quantitative synthesis (meta-analysis) (n = 11)

Full-text articles excluded (n = 4), with reasons of focus on diseases other than dermatological

Figure 1: Prisma Flow Diagram

## Studies Inclusion and Exclusion Criteria

Table 4: Selection of studies based on inclusion and exclusion criteria

|  |  |
| --- | --- |
| Inclusion criteria | 1. Studies discussing different machine learning models to classify skin diseases 2. Articles published in journals were included 3. Only the newest version of an article was included if and when there were duplicates |
| Exclusion criteria | 1. Articles not in English 2. Articles discussing the detection and classification of diseases other than dermatological ones |

Introduction

*Image processing and computer vision*

Images are represented by their dimensions, height and width. A digital image contains pixels. The points in the image that have certain colors or shades are what is referred to as pixels. A digital image is a function that is represented by a 2D integer array, or a series of 2D arrays, one for each color band. Pixels are elements of the array. Normally, the size of the array is a few hundred pixels by a few hundred pixels [Petrou2010].

Image processing, in essence, is the application of signal processing techniques where the input is an image, like a photograph or a video frame, and the output is another image, or a set of characteristics related to the image. This way useful information is retrieved from the image. Usually, image processing refers to digital image processing, although analog image processing is also available. While analog image processing is an image processing task that uses 2D analog signals, digital image processing uses computer algorithms. As such, digital image processing is more beneficial since it can avoid various problems, including signal distortion or noise buildup, by enabling the application of numerous algorithms on the input data. To process images digitally, the image needs to be digitized. For an image to be in digitized form, the analog image is sampled on a discrete grid with each pixel quantized using a finite number of bits. A computer can then process this image [Lu2017].

In the past few years, image processing has become popular when it comes to acquiring accurate data for computer processing, reducing computational costs, as well as enhancing understanding. Image processing is used for several different tasks. Some of these tasks include image enhancement, image restoration, image segmentation, object detection, image compression, image manipulation, and many more [Thakur2023].

As a closely related concept to image processing, computer vision is considered high-level image processing as it allows computers to identify and understand physical objects within an image. Its aim is to replicate the way human vision works. For this reason, computer vision applications are trained using massive amounts of visual data to recognize patterns and then determine the content of other images using those patterns. Seeing as this capability can be very beneficial, it finds use in different spheres, such as agriculture, healthcare, facial recognition, augmented reality, manufacturing, and so on [Azure2024].

*Dermatological diseases*

As the organ that covers the muscles, bones and all the parts of the body, skin is the largest organ of the human body. Being exposed to the environment makes the skin prone to getting infected or catching diseases. Any condition that damages, clogs or irritates the skin, including skin cancer, is referred to as a skin disease. Some of these diseases are inherited, while others may develop later in life due to various reasons [Healthline2024].

Besides life conditions and different lifestyle factors, common causes of dermatological disorders include viruses, fungus and parasites, contact with allergens and irritants, bacteria trapped in skin pores, illnesses that affect the immune system, thyroid and kidneys, and many more. Some commonly known skin diseases involve rosacea, acne, eczema, cellulitis, melanoma, lupus, chickenpox, and so on. While some of these diseases are temporary, others are chronic and may even be life threatening, such as skin cancer. Even though chronic skin diseases, like rosacea, vitiligo, cannot be cured, they can still be treated to help patients manage the symptoms better. The symptoms of skin disorders can vary greatly from disease to disease. Typical symptoms are rashes, red or white raised bumps, ulcers, discolored skin patches, fleshy bumps or warts, changes in mole color and size, and more [Healthline2024].

Although a few disorders, like the genetic ones and the ones caused by illnesses, cannot be prevented, the others can easily be prevented by following some basic hygiene measures, such as washing hands frequently, avoiding contact with infected people, getting vaccinated, avoiding sharing personal things [Healthline2024].

*Studies related to the topic of dermatological diseases detection through image processing*

Detecting skin diseases, especially skin cancers, at an early stage is crucial, as it prevents the progression of the disease. To determine the condition and its stage, primary screening control of patients is carried out. This diagnosis is done visually, and is sometimes followed by dermoscopic analysis, biopsy and histopathological examination. To make the diagnosis process simpler and to avoid physical contact with the skin altogether, computer aided-diagnosis methods were developed. These methods are able to detect dermatological diseases by analyzing an image of the lesion [Udristoiu2020]. Although there are various claims that computer-based systems are more accurate than dermatologists when diagnosing dermatological diseases, they are still in the early stages of clinical application where they help experts in the diagnosis process. In cases when a disease is confirmed by a computer-based system, a biopsy and histological test are still needed to confirm the diagnosis. This comes due to the fact that sometimes these systems can misdiagnose or misinterpret the images due to numerous reasons, such as noisy data, race and ethnicity, mimics of skin lesions, and so on [Goyal2020].

The first step to analyzing skin lesions is by pre-processing the image. The aim of pre-processing is to enhance the image. The next step is the segmentation of the image which subdivides the image into regions. Once the segmentation is done, the color and the texture features of the lesions are extracted. In this case, the texture features are crucial as they help identify skin diseases easily by providing information regarding the pattern or consistency on the skin. When the features are extracted, a test sample of one of the known classes is used to train a classifier of choice. The performance of the classifier is then measured and evaluated [Sumithra2015].

In their study, [Araaf2023] et al. focused on identifying and classifying the two types of skin cancer, malignant and benign. To achieve this, they gathered 3297 images of benign and malignant skin cancer from Kaggle.com. First, they preprocessed the images of the dataset using grayscale and average filter. This way, the images were converted into grayscale images and the noise was reduced from them to ensure emphasis on the main characteristics of the object. Once the images were preprocessed, feature extraction was applied to produce values for contrast, correlations, dissimilarity, energy and homogeneity. After the feature extraction, K-Nearest Neighbor algorithm was used to classify the images. The results of the classification show that the algorithm has accuracy of 76%. The accuracy, however, increases on smaller datasets. This happens due to the algorithm’s nature of avoiding overfitting. Although the accuracy of the algorithm is not a satisfactory result, this study provides some interesting findings such as the increased accuracy after implementation on smaller datasets, the application of the average filter, and the role of dissimilarity features.

Another study that uses K-Nearest Neighbors algorithm to classify dermatological diseases is the one by [Sumithra2015] et al. Besides this algorithm, they also use SVM so they can compare the performance of each algorithm, as well as the performance of the fusion of the algorithms. After collecting images from the Internet for five different diseases (melanoma, bullae, seborrheic keratosis, shingles and squamous cell), the images were segmented using the region growing method. Afterwards, the color and texture features of the images were extracted. Once this was done, classification took place in five different sets where experiments were repeated 20 times with randomly chosen training samples. The results of the study indicate that the SVM algorithm achieves a better performance in terms of accuracy than the kNN algorithm, whereas the best performance is achieved by the fusion of SVM and kNN. The authors propose that the SVM-kNN fusion be used to diagnose skin diseases by experts as a supplementary tool.

In their work, [Udristoiu2020] et al. developed a deep learning algorithm that can help dermatologists diagnose skin conditions. For this, they selected a dataset with more than 10000 images of seven categories of lesions: actinic keratoses and intraepithelial carcinoma/Bowen's disease, basal cell carcinoma, benign keratosis-like lesions, dermatofibroma, melanoma, melanocytic nevi, and vascular lesions. The data contained in the dataset was augmented and divided into training and testing sets. The model that was developed and used for the diagnosis of dermatoscopic images is a four-layer convolutive model (4-CNN). After training and testing the model, its performance is measured using the following metrics: precision, sensitivity, specificity, test accuracy and area under the curve. The results of the study show that the model achieved accuracy of 93.6%, precision of 91%, specificity of 98.3% and sensitivity of 95.9%.

The goal of the study by [Srinivasu2021] is to design an app which captures the image of the infected skin region and classifies the skin disease. To achieve this, they used a dataset found on Kaggle which has more than 10000 images. These images belong to seven different skin diseases: melanocytic nevi, benign keratosis-like lesions, dermatofibroma, vascular lesions, actinic keratoses, intraepithelial carcinoma, basal cell carcinoma, and melanoma. Due to the imbalance in the dataset where some diseases are more represented than others, data was augmented and then divided into training and testing sets. The model chosen to classify skin diseases is MobileNet V2 integrated with LSTM. MobileNet V2 is used to classify skin diseases, whereas LSTM maintains the state information of the features from the previous generation of the image classification, thus enhancing the performance of the model. After training and testing the model, the performance of the model was measured in terms of accuracy. The results show an accuracy of 85.34%. However, the model’s accuracy decreases to less than 80% when using poorly illuminated photographs to train and test it.

In their work, [Lopez2017] et al. used the VGGNet convolutional neural network to classify skin lesions. The dataset used for this task is the skin lesion analysis dataset by the International Symposium on Biomedical Imaging (ISBI). The data found on the dataset was preprocessed and augmented. Since the VGGNet model can be used in three different ways, the authors proposed three different methods: training the model from scratch, leveraging features from a pre-trained VGGNet on a larger dataset using the transfer learning paradigm, and fine-tuning the architecture of the model and keeping the transfer learning paradigm. To measure the performance of the model for each method, loss, sensitivity, precision, specificity and accuracy were used as metrics. The model was then trained and tested in 20 epochs for each method. Out of the three methods, the third one performed best with an accuracy of 81.33% and a sensitivity of 78.66%. This comes due to the reduced dependency on the images’ initialization weights. In comparison, the second method, with low performance on loss, sensitivity and accuracy, presents an example of overfitting since it prioritizes decreasing the processing time.

1. **PRACTICAL TASK**

# Task specification

The practical task’s goal is to identify and classify dermatological diseases based on the images provided. To achieve this, a simple classifying system was created using Python. The idea behind the system is that if the user adds the path to the dermoscopic image in the prompt and presses “Enter”, the system will predict the disease based on the image provided. To create this system, two models were developed and compared to see which one has the best performance. The algorithms that were developed are SVM and Random Forest Classifier. These algorithms were then compared based on accuracy and precision in classifying diseases.

Data and tools

The dataset used for this task is called “Skin-Disease-Dataset”. It can be found under the following link: https://www.kaggle.com/datasets/subirbiswas19/skin-disease-dataset. The downloaded folder contains 1159 image files separated into two sets of data, the training set and the test set (80-20). The images are divided into eight different classes, depending on the pathogen involved in the skin infection (bacterial, fungal, parasitic, viral). To represent each pathogen, one or two typical diseases were added. The classes include bacterial infections – cellulitis and impetigo, fungal infections – athlete-foot, nail fungus and ringworm, parasitic infections – cutaneous larva migrans, viral infections – chickenpox and shingles. The images that are part of this dataset were collected from the Internet.

Many studies stumbled upon while conducting the literature review stated that the dataset used for their papers was the HAM10000 dataset. This dataset contains more than 10000 images of benign and malign skin tumors. Apart from the fact that this dataset is too big and would take very long to process, it also only contains data about skin tumors and no other diseases. As I found it more interesting to compare the classification of various dermatological diseases, Kaggle was referred to for a more suitable dataset. After going through many datasets, the “Skin-Disease-Dataset” was selected as it represents eight different diseases that are clearly labelled.

For this task, all the data contained in the dataset was used. All 1159 images found in the dataset were preprocessed and their features were extracted. These features were in turn used to train and test the SVM and Random Forest Classifier models with the purpose of classifying dermatological diseases.

A close-up of a leg

Description automatically generated Figure 2: Cellulitis A close-up of a person's chin

Description automatically generated Figure 3: Impetigo

Close-up of a pair of feet

Description automatically generated Figure 4: Athlete foot A close up of a toenail

Description automatically generated Figure 5: Nail fungus

A close-up of a blister

Description automatically generated Figure 6: Ringworm A person with red spots on their back

Description automatically generated Figure 7: Chicken pox

A close-up of a foot with a scar

Description automatically generated Figure 8: Cutaneous larva migrans A close-up of a skin rash

Description automatically generated Figure 9: Shingles

*Data constraints*

The dataset contains more than 1000 images divided into two folders, training and testing data. Although the data was easily accessible and clearly labelled, the process of using the data was not seamless. First, while working on the practical task, it was noticed that there is a dataset imbalance as some classes are more represented than others. This data discrepancy affects the model accuracy by causing the model to struggle when recognizing different diseases. Another issue that was noticed was the presence of noise in images. Some images in the dataset contained watermarks that might confuse the model and affect its accuracy. An additional factor that might affect the model’s accuracy is the similarity between the symptoms of some diseases, which in turn leads to the model confusing the diseases with one another.

An issue worth mentioning is that the images in the dataset are not visually pleasant and not easy to look at for people who are not involved or interested in medicine. For this reason, going through the different classes of the dataset and analyzing the images contained in them was a bit difficult.

Implementation

Research on the topic of classifying dermatological diseases based on dermoscopic images was conducted and a suitable dataset was chosen for the task at hand. Once this was done, a few different models were developed and compared to see which one is more appropriate for the task. The models that were developed are SVM and Random Forest Classifier. A comparison of the algorithms based on their accuracy and precision was necessary to see which one is the best algorithm to classify skin diseases based on dermoscopic images.

The link to the code on GitHub:

*System implementation*

The first step to implementing the system was to import the libraries needed:

* Numpy, which handles numerical computations
* Matplotlib, which is used for data visualization
* Seaborn, which is used for advanced data visualization
* Os, which is used to navigate file directories
* Sklearn, which is used for preprocessing, model training, and evaluation
* StandardScaler, which is used to standardize feature values
* Train\_test\_split, which splits the dataset into training and testing sets

Once the necessary libraries were imported, the data needed to be preprocessed. In this step, the images were loaded, and their sizes were adjusted to 299x299 pixels as this is the required input by the InceptionV3 model used as a basis for both algorithms. These images were then converted to numpy arrays, and the pixel values were normalized by 255.0, which scales the pixel values between 0 and 1. In addition, labels based on folder names were generated.

A computer screen shot of a program code

Description automatically generated

Figure 10: Data preprocessing

Next, using InceptionV3, a CNN model, the features for each image were extracted and standardized. The standardization of the features scales the features into having a mean of 0 and a standard deviation of 1. This improves the performance of SVM as this model is sensitive to feature scaling.

A screen shot of a computer program

Description automatically generated

Figure 11: Feature extraction and standardization

Next, the data was split into data that is used to train the model (80%) and data that is used to test the model (20%). Once the dataset was split, the model was trained and evaluated. This was done by generating a classification report which provides detailed metrics for each class and by generating a confusion matrix which visualizes the correct and incorrect predictions of the model.

A computer screen shot of text

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Figure 12: SVM model training and evaluation

In the end, to see how this model works, an interactive prompt was developed. This prompt asks the user for the path to the desired image and once the user presses “Enter” the system will load and preprocess the image, as well as extract the features of the image and scale them. Using the trained SVM model, the system predicts the class of the disease shown in the image and prints it along with the confidence of the prediction made.

A computer screen shot of a program code

Description automatically generated

Figure 13: Interactive prompt

The same steps were followed when developing and implementing the Random Forest Classifier algorithm. The only part where it differs is in the model training part where instead of the SVM model, the Random Forest Classifier model was trained.

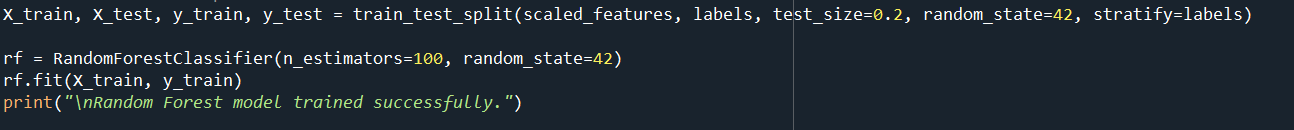


Figure 14: Random Forest Classifier model training

*Results*

When the system implementation was finished, the system’s performance had to be tested. For this, the accuracy of the model was evaluated to see how well the models perform with the given dataset.

1.SVM

When evaluating the SVM model using the test set, the model displayed an accuracy of 91.89% (0.92). This high value indicates that the system performs very well when classifying skin diseases based on the given images. The results of the classification report were quite satisfactory. On the table below, the results of each disease for precision, recall, F1-score and support are displayed, as well as the results of the SVM model in terms of accuracy, macro average and weighted average. In addition, the confusion matrix shows good results with minimal incorrect predictions.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Class** | **Precision** | **Recall** | **F1-Score** | **Support** |
| BA – Cellulitis | 0.96 | 0.96 | 0.96 | 27 |
| BA - Impetigo | 0.88 | 0.88 | 0.88 | 16 |
| FU – Athlete foot | 0.80 | 0.96 | 0.87 | 25 |
| FU – Nail fungus | 1.00 | 1.00 | 1.00 | 26 |
| FU – Ringworm | 0.94 | 0.83 | 0.88 | 18 |
| PA – Cutaneous larva migrans | 0.87 | 0.65 | 0.74 | 20 |
| VI – Chickenpox | 1.00 | 0.96 | 0.98 | 27 |
| VI - Shingles | 0.90 | 1.00 | 0.95 | 26 |

Table 5: Classification report for SVM

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Accuracy |  |  | 0.92 | 185 |
| Macro avg | 0.92 | 0.91 | 0.91 | 185 |
| Weighted avg | 0.92 | 0.92 | 0.92 | 185 |

Table 6: Results of the SVM model

A graph of a number of different types of cells

Description automatically generated with medium confidenceFigure 15: Confusion matrix for SVM

The results depicted on the classification report indicate an overall good performance of the SVM model for each disease. The highest precision value reached by the model is 1.00 in the cases of FU – Nail fungus and VI – Chickenpox. This means that the SVM model does not predict false positives for these two classes. As for the other classes, the precision value is quite high which means that the number of false positives predicted by the model is minimal. The recall metric reaches its maximum value of 1.00 for the classes FU – Nail fungus and VI -Shingles. In the case of these two classes the SVM model is able to capture all the actual positives. In general, the precision score is high for all the classes, except for the PA – Cutaneous larva migrans where the value is significantly lower (0.65). As for the F1-Score, the SVM model achieves a 1.00 score for the FU – Nail fungus class. The rest of the classes show high F1-Score values as well. These results show that the highest performing classes are FU – Nail fungus, with a perfect score of 1.00 for each metric, VI – Chickenpox and BA - Cellulitis. On the other hand, the lowest performing classes include PA – Cutaneous larva migrans, with lower recall and F1-score values, and FU – Ringworm, with somewhat lower values for each metric. Overall, the SVM model displays an accuracy of 91.89%, which shows that the model can predict accurately 91.89% of all the test samples. The macro average values are high for each metric, which indicates a good performance of the model across all the classes on average.

2.Random Forest Classifier

On the other hand, when evaluating the Random Forest Classifier model using the test set, the model showed an accuracy of 90.27%. Although the high value of the accuracy shows that the system performs very well when classifying skin diseases based on images, this value is slightly lower than the accuracy of the SVM model. The classification report and the confusion matrix show satisfactory results of the model, and these are displayed on the table and image below. In addition, the results of the Random Forest Classifier in terms of accuracy, macro average and weighted average are displayed,

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Class** | **Precision** | **Recall** | **F1-Score** | **Support** |
| BA – Cellulitis | 0.84 | 1.00 | 0.92 | 27 |
| BA - Impetigo | 0.93 | 0.81 | 0.87 | 16 |
| FU – Athlete foot | 0.81 | 0.88 | 0.85 | 25 |
| FU – Nail fungus | 0.93 | 0.96 | 0.94 | 26 |
| FU – Ringworm | 1.00 | 0.89 | 0.94 | 18 |
| PA – Cutaneous larva migrans | 0.80 | 0.60 | 0.69 | 20 |
| VI – Chickenpox | 0.96 | 1.00 | 0.98 | 27 |
| VI - Shingles | 0.96 | 0.96 | 0.96 | 26 |

Table 7: Classification report for Random Forest Classifier

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Accuracy |  |  | 0.90 | 185 |
| Macro avg | 0.90 | 0.89 | 0.89 | 185 |
| Weighted avg | 0.90 | 0.90 | 0.90 | 185 |

Table 8: Results of the Random Forest Classifier model

A graph with blue squares and white text

Description automatically generated

Figure 16: Confusion matrix for Random Forest Classifier

According to the results shown on the classification report, the Random Forest Classifier model exhibits an overall good performance for each disease. The precision metric achieves the highest value for the FU – Ringworm class, which indicates that the model predicts no false positives for this class. The value of this metric is high for all the other classes as well, suggesting a minimal number of predicted false positives. As for the recall metric, it reaches the maximal value of 1.00 for the classes BA – Cellulitis and VI – Chickenpox, indicating the model captures all the actual positives. The recall score maintains high values overall except for the PA – Cutaneous larva migrans class, where the value of the metric reaches 0.60. The highest F1-Score the model achieves is 0.98 in the case of the VI – Chickenpox class. The values of the metric are quite high across the classes besides in the case of the PA – Cutaneous larva migrans class, where the F1-Score value is lower in comparison (0.69). The results shown on the classification report suggest that the BA – Cellulitis class is the highest performing one with almost perfect values for the metrics. Other high performing classes include FU – Nail fungus, FU – Ringworm and VI – Chickenpox. Low performing classes include PA – Cutaneous larva migrans and BA – Impetigo. Overall, the Random Forest Classifier model shows an accuracy of 90.27%, which indicates the model predicts accurately 90.27% of all the test samples. Although this is a very satisfactory result, it is slightly lower than the results of the SVM model (91.89%). The high macro average values show that the model has a good performance across all the classes on average, however there are inconsistencies in recall, especially in the case of the PA – Cutaneous larva migrans class.

*Discussion*

The initial idea of this paper was to classify dermatological diseases based on the provided images of skin lesions. In order to see how well the system performs, an interactive prompt was to be developed and displayed for the user to enter the oath to the desired image and the system would predict the disease class. For this, two different models, SVM and Random Forest Classifier, were developed and their performance was compared to see which one is the better model. The SVM model displayed an accuracy of 92%, whereas the Random Forest Classifier showed an accuracy of 90%. Because of the slight difference in accuracy, the SVM model was chosen to be used for the interactive system.

To make the interactive system possible, the function interactive\_prediction was defined within the SVM model code file. The way this system works is it asks the user to input the path to an image and then loads, preprocesses and extracts the features of said image using InceptionV3. Next, the system predicts the class of the image using SVM and displays it along with the confidence score. In case the path to the image is incorrect or invalid, the system will display a message letting the user know that the path was not valid.

A computer screen shot of a program

Description automatically generated

Figure 17: Interactive prediction function

After testing the system with more than 15 images, it is concluded that the system is highly accurate as it predicted most of the images accurately with a high confidence score. Out of the trials conducted, the system was inaccurate only once. In this case, the system was given the path to an image from the PA – Cutaneous larva migrans class and it inaccurately predicted it to be from the FU – Athlete foot class.

A computer screen shot of a program

Description automatically generated

Figure 18: System prediction 1

A screen shot of a computer program

Description automatically generated

Figure 19: System prediction 2

Although the system is highly accurate when predicting dermatological diseases, there are still a few weaknesses. The model seems to have class-specific issues and cannot accurately predict the class of the image when it comes to the PA – Cutaneous larva migrans and FU – Ringworm classes. This inaccuracy can happen due to various reasons. One of the main reasons for this is the dataset imbalance. The support in the PA – Cutaneous larva migrans and FU – Ringworm classes is relatively low compared to the other classes. The lower number of samples of these classes causes the model to be more accurate when predicting classes that are well represented in comparison to underrepresented classes. Another issue is the similarity of some classes with other classes. For example, skin lesions of PA – Cutaneous larva migrans could be somewhat similar to other diseases, such as FU – Ringworm or FU – Athlete foot. This makes it difficult for the model to distinguish between the different diseases. Another identified issue is the presence of watermarks in some images. This noise presence in the images makes it harder for the model to classify diseases as it reduces the model’s ability to generalize and identify the symptoms.

Conclusion

Detecting and classifying dermatological diseases based on dermoscopic images can be very helpful for dermatologists as it helps them identify the disease without direct contact with the skin. The literature review conducted revealed that there are plenty of articles online related to this topic, however there is a lot of room for improvement and research to be done. As they still may misdiagnose or misinterpret image skin lesions due to various reasons, these computer-based systems are still in the early stages of clinical application. The majority of the existing research suggests that using convolutional neural networks is the best way to detect and classify dermatological diseases. For the practical task of this paper, a predictive system using Python was created. To achieve this, a dataset with eight different diseases was chosen. After preprocessing and extracting the features of the images using InceptionV3, a CNN model, two different models, SVM and Random Forest Classifier, were compared based on their accuracy. SVM displayed an accuracy of 92%, while Random Forest Classifier displayed an accuracy of 90%. For this reason, SVM was used to further create an interactive prompt for the user to see how well the model works. Although the accuracy of the model is satisfactory, there are cases when the model is not very accurate, as is the case with the PA – Cutaneous larva migrans class. This comes as a result of many factors, such as dataset imbalance, symptom similarity, noise presence in the images and so on.

Bibliography and references

## List of tables

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## List of abbreviations

BA – Bacterial infections

CNN – Convolutional Neural Networks

FU – Fungal infections

PA – Parasitic infections

SVM – Support Vector Machines

VI – Viral infections

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