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Classification of Skin Disease using Machine Learning Techniques

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ABSTRACT

Due to their complexity and time-consuming process, skin diseases can be difficult to diagnose in the global health community. Undiagnosed and uncontrolled skin diseases have adverse effects on human health and psychological well-being. With today's technology, it is possible to diagnose skin diseases quickly and easily using image processing and machine learning techniques. The article describes a method for diagnosing Actinic Keratosis , Atopic Dermatitis, Dermatofibroma, and Melanoma based on the image of the skin. This model involves five steps, the acquisition of images, the pre-processing, the segmentation, and the feature extraction. We also evaluated the model using machine learning algorithms, such as Support Vector Machines (SVMs), Random Forests (RFs), and K-Nearest Neighbors (K-NNs), and achieved 86.4%, 81.48%, and 59.25% of accuracy, respectively. Comparisons were made between the SVM classification results of the proposed model and those of other papers, and the proposed model generally performed better.

Keywords: Machine learning, Skin disease, Image processing, Diagnosis and classification.

INTRODUCTION

Skin diseases come in a variety of forms and forms, as well as being caused by many factors [1]. The hormones in our body and the glands in our body can cause acne, while the air pollution we breathe or our sensitivity to the sun can cause rashes. In addition to scabies, lice, drug allergies, rosacea, psoriasis, eczema, sweet syndrome, and ofuji disease, there are various types of skin diseases that can occur, some of which are contagious and some not. A common misconception about skin diseases is that they are not important when they happen, and it is better not to visit the doctor when they do.

A total of 1.79% of all physical disabilities are caused by skin diseases in all countries of the world. Different countries suffer from different types of skin problems, affecting 30% to 70% of the population [2]. This occurs when a specific skin injury is not treated while cells respond abnormally to ultraviolet light from the sun or when they are exposed to specific skin injuries. According to recent statistics, cancer ranks second among human causes of death. In countries with low living incomes, approximately nine million people die each year. Because specialized doctors weren't consulted at the beginning, the disease developed into an advanced form of cancer that is becoming increasingly difficult to treat [3]. There is a relationship between skin diseases and society, and both are impacted by each other. The aesthetic aspect of it is also included. The importance of skin diseases in pathology has attracted researchers from around the world to research automatic diagnoses. Similarly, rapid technological

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advancements and their impact on all fields, especially in medicine, is of the utmost importance. With the help of machine learning algorithms and deep learning algorithms, automated disease diagnostic tools can be designed based on healthcare data. Researchers have been able to train classifiers that can perform machine diagnostics by combining machine learning and deep learning principles. Artificial intelligence, deep learning, and machine learning are all connected in a progressive process. Based on a wealth of data, Deep Learning algorithms solve data and create new accounts using Machine Learning and Neural Networks. Data from Machine Learning is used to provide this information. Artificial Intelligence is the result of combining several Machine Learning algorithms into one device. In addition to developing and preparing medicines and treatments, researchers can use patient records to discover when and how diseases spread. The quality of health care in rural and village areas is poor, and dermatologists are in short supply [4]. Diagnoses are made by non-trained staff in those areas. A person with a skin disease has to pay a high amount for medical professionals to monitor his or her condition. Technical systems that use images are required to determine how severely injured a patient is. In a group of diseases that are difficult to diagnose with images, machine learning algorithms have been used to categorize skin lesions according to their shape at different stages of their lives [5]. There are many dermatitis that can cause psoriasis, including seborrheic dermatitis, pityriasis rosea, and chronic dermatitis, such as pityriasis rubra.

Clinical characteristics and histopathological characteristics are used to determine the severity of a disease. Due to the ability to simulate human behavior in prediction, expert systems have greatly improved the accuracy and efficiency of skin disease diagnosis [6]. Symptoms of skin diseases are long-term and constantly changing, so evaluating changes since the initial appearance of the lesion is crucial to diagnosing the disease. Skin conditions can lead to serious health risks, which are often overlooked by people. By combining self-learning algorithms with sophisticated data visualization techniques, artificial intelligence can provide real-time, extensible, and unique medical care. Five research areas are currently focused on dermatology: Precision Medicine - Classifying skin diseases using clinical images - Classifying skin diseases using dermatopathology images - Using smartphone apps and monitors to diagnose skin diseases - Epidemic disease research facilities [7]. To prevent harming the patient's safety, a medical classifier must be confident that it can accurately predict the type of disease by predicting a high percentage, and on the other hand, pass along the diagnosis to a doctor. A number of important medical systems have been developed as a result of the Internet of Things [8]. Through the use of this technology, doctors are now able to diagnose patients in multiple locations without having to worry about subjective factors getting in the way. Smart systems that can diagnose diseases like professionals can be developed using this technology. When a system is designed to identify rare and common diseases, however, a data imbalance must be addressed in order to be effective.

RELATED WORK

Research has been conducted to develop a machine learning algorithm and image processing model that can be used to categorize and diagnose a wide range of skin diseases.

According to Hameed, Shabut, and Hossain, five types of skin disorders exist: benign skin, acne, eczema, psoriasis, and melanoma (malignant) [9]. In order to construct the system, image processing techniques were used. They removed hair from skin images using the Dull Razor algorithm in order to improve images, and then smoothed them using the Gaussian filter. Otsu's thresholding was applied to the skin area following the removal of any non-skin areas after the non-skin areas were discarded. In addition, the brightness of colors was distinguished by the RGB color model, hue, saturation, and value (HSV), as well as the luma, blue, and red color model (YCbCr).

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Furthermore, they analyzed texture features using Neighborhood Gray-Tones Difference Matrixes (NGTDMs) and Gray Level Co-occurrence Matrixes (GLCMs). Their final classification of the diseases was 83% accurate using SVM.

A method for detecting skin diseases is also proposed by Ahammed et al [10]. In their method, noise is removed using an adaptive filter, then the grayscale color is converted. Furthermore, the disease lesion was segmented using Otsu's thresholding technique. In addition, the texture features were extracted using GLCM. Finally, the SVM classifier was used to test their proposal and achieved 89% accuracy. A K-NN classification algorithm is used by the research group in image classification-based color to detect and classify different types of skin diseases [11]. Color models such as HSV, red/green, blue/yellow, and lightness are used for feature extraction. HSV color models perform better with 90.60% accuracy than Lab color models with 81.60% accuracy, according to their results. Additionally, Ahmed, Ema, and Islam propose an automated method for classifying 24 types of skin diseases using the Transductive SVM (TSVM). Segmenting images in the proposed system is based on hybrid genetic algorithms. Additionally, ant colony optimization (ACO-GA) and GLCM were used to extract the features. Their work achieved an accuracy rate of 95%.

In order to extract skin disease characteristics, pre-trained Convolutional Neural Networks (CNN) were analyzed [12]. Alenezi proposes a system for extracting skin disease features from CNN AlexNet and classifying them using SVMs. For the development of the system, 81 images of melanoma, psoriasis, eczema, and healthy skin were collected. An accuracy of 100% was achieved on 20 images by her system. In the same study, researchers created an intelligent expert system that classifies 9145 lesions, including acne, eczema, benign (melanoma), and healthy skin pictures [13]. To extract features from the lesion, the researchers used a CNN model pre-trained by AlexNet. The system was trained and tested using a SVM classifier, with a ratio of 71:32, resulting in an accuracy of 85.20 percent.

An algorithm is proposed in a second study to detect 405 images of skin diseases, such as eczema, impetigo, and melanoma, as well as a class of images titled other [14]. For this model, noise was removed using median filtering, lesions were isolated using Otsu segmentation, texture features were extracted using GLCM, and entropy and standard deviation were extracted using 2D Wavelet transform.

91.7% and 96.1% accuracy were achieved with SVM and CNN classifiers, respectively. CNN classifiers and image processing libraries are described by the authors in the article [15].

There may be a 92% increase in accuracy when using a large dataset. Skin diseases can be classified and diagnosed using CNN with an accuracy of 71%. In their paper, the authors propose a web-based skin disease diagnosis system [16]. A CNN image classification algorithm was used to identify atopic dermatitis, acne vulgaris, and scabies from 254 images. A total of 87% accuracy was achieved for each disease, 84% accuracy for heart disease, and 82.7% accuracy for cancer [17]. Diagnoses may be made faster than a clinic diagnosis by using the proposed system, which takes only 0.0001 seconds to complete. SVMs and CNNs have been shown to be effective in many previous studies. Additionally, the studies revealed that image processing is essential for classifying various skin diseases. Due to the increased training model, the number of images may also have a positive effect on the classification.

METHODOLOGY

A classification of various skin diseases is used in this publication to demonstrate the diagnosis of skin cancers, Actinic Keratosis , Atopic Dermatitis, Dermatofibroma, and Melanoma .It is therefore necessary to perform preprocessing, segmentation, feature extraction, and classification to identify these skin disorders. In the following sections, we explain the datasets we used and the methodologies we used.

Dataset :- Due to the sensitive nature of medical records, acquiring images for research can be challenging. This study utilized publicly available resources, specifically the dermnet NZ [14] to obtain

Journal of Information Systems Engineering and Management
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https://www.jisem-journal.com/ **Research Article**

a dataset of 402 images. These images were categorized into four disease classes: Actinic Keratosis , Atopic Dermatitis, Dermatofibroma, and Melanoma Fig. 1 showcases a sample image from each class, while Table I provides a class-wise image distribution.

Disease Definitions:-

- **Actinic Keratosis:** Actinic keratosis is a rough, scaly patch on the skin caused by long-term exposure to the sun. It is considered a precancerous condition because it can sometimes develop into squamous cell carcinoma, a type of skin cancer. Areas frequently exposed to the sun, such as the face, scalp, ears, neck, forearms, and back of the hands.
Symptoms:
- Rough or dry patches on the skin, often less than an inch in diameter.
- Lesions may be pink, red, or brownish in color.
- Itchy or tender skin in the affected area.

- **Atopic Dermatitis:** Atopic dermatitis (AD) is a chronic inflammatory skin condition characterized by itchy, red, and swollen skin. It is the most common type of eczema and is associated with a genetic predisposition and environmental triggers. Face, neck, hands, feet, and the insides of elbows and knees.
Symptoms:
- Red, itchy, and inflamed skin.
- Cracked or scaly patches, often accompanied by oozing or crusting.
- Common in children but can occur at any age.

- **Dermatofibroma:** Dermatofibroma is a benign, non-cancerous growth of fibrous tissue that commonly appears on the skin. It often results from minor injuries like insect bites or trauma.
Symptoms:
- Firm, round, or oval-shaped bump on the skin, typically less than 1 cm in diameter.
- May be red, brown, or skin-colored.
- Often asymptomatic but can sometimes itch or be tender.

- **Melanoma:** Melanoma is the most serious type of skin cancer, developing in the melanocytes, the cells that produce melanin (the pigment that gives skin its color). If not detected early, melanoma can spread to other parts of the body.
Symptoms:
- A new mole or a change in an existing mole (size, shape, or color).
- Irregular edges, multiple colors, or asymmetry in a mole.
- Moles larger than 6 mm in diameter.
- Itching, bleeding, or crusting moles.

Fig 1- Datasets Sample

Journal of Information Systems Engineering and Management
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Disease	Dataset	Total
Actinic Keratosis	Dermnet NZ Dataset	100
Atopic Dermatitis	Dermnet NZ Dataset	102
Dermatofibroma	Dermnet NZ Dataset	100
Melanoma	Dermnet NZ Dataset	100
Total		402

Table 1 – Dataset Distribution

A. Proposed Methodology

This section outlines the methodology employed in the proposed skin disease diagnosis model, as illustrated in Fig. 2.

1. Image Processing:

- **Preprocessing:**
  - Images are resized to 250x250 pixels for uniformity.
  - A median filter removes noise while preserving edges.
  - Color images are converted to grayscale for simplified analysis.
  - Pixel values are normalized to a range of 0 to 1.
- **Segmentation:**
  - Otsu's thresholding technique is used to create a binary mask, isolating the lesion from the surrounding skin.
  - This step is crucial but challenging due to variations in lesion appearance and the complexity of skin textures.

2. Feature Extraction:

- Relevant features are extracted from the segmented lesion images.
- These extracted features are stored in a knowledge base for subsequent classification.

3. Classification:

- Machine learning algorithms, including Support Vector Machines (SVM), Random Forests (RF), and K-Nearest Neighbors (K-NN), are employed to classify the images based on the extracted features.

4. Diagnosis:

- The model diagnoses the skin condition based on the classification results.

5. User Image Processing:

- When a user uploads an image, it undergoes the same preprocessing and segmentation steps as the training data.

Key Improvements:

- **Conciseness:** Removed redundant phrases and streamlined the language.
- **Clarity:** Improved sentence structure and flow for better readability.

Journal of Information Systems Engineering and Management
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https://www.jisem-journal.com/ **Research Article**

- **Focus:** Emphasized the key steps and their significance.
- **Consistency:** Maintained consistent terminology and formatting throughout the text.
- **Brevity:** Reduced the overall length of the text while retaining essential information.

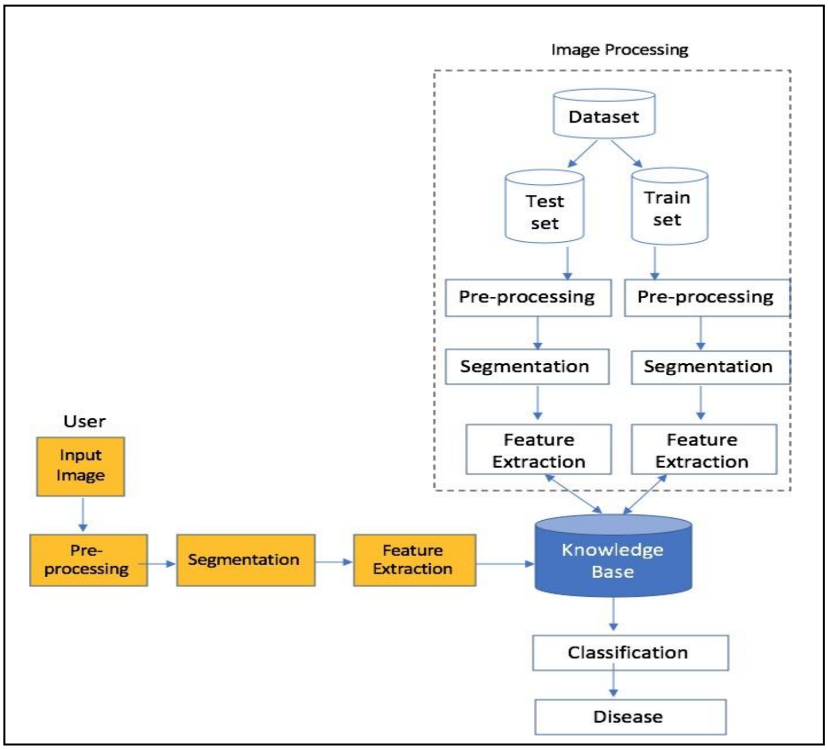
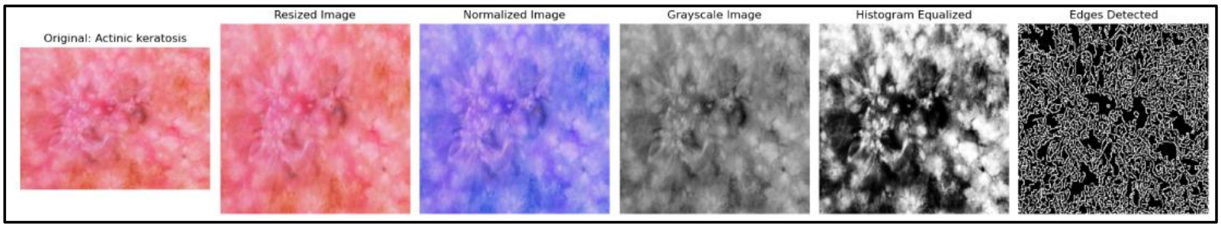
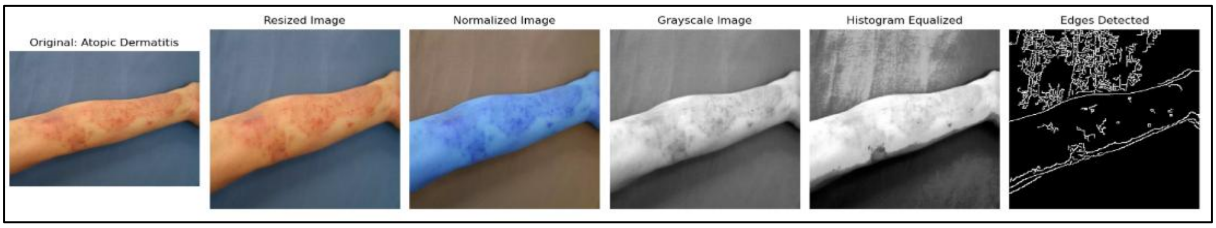
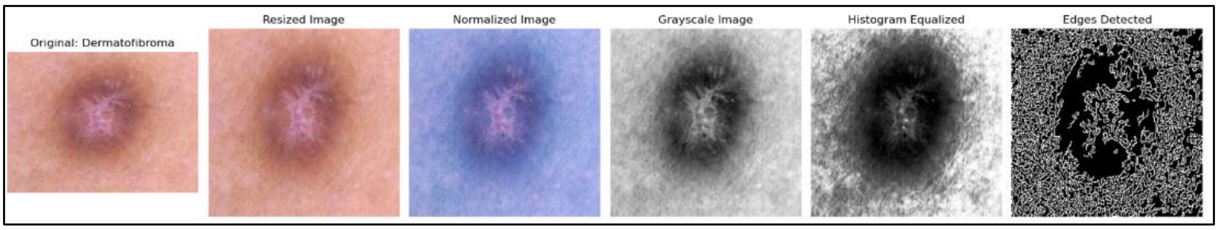


Fig2. Model Architecture







Journal of Information Systems Engineering and Management
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https://www.jisem-journal.com/ **Research Article**

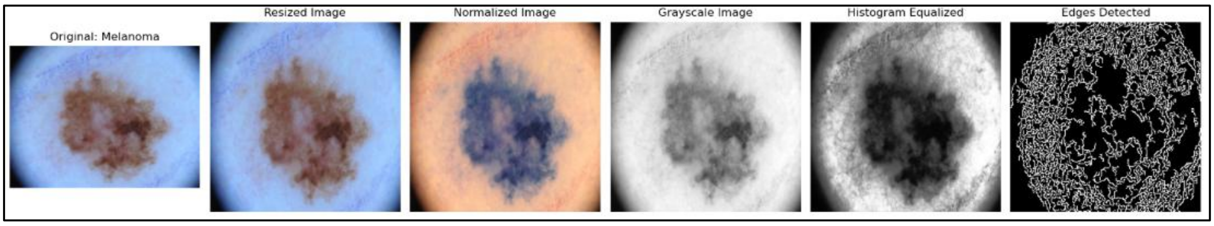

Fig3- Images Processing Techniques Sample Results

In this study, each disease was briefly summarized on the dermnet NZ website. In addition to affecting the face, back, chest, and neck, it is a common chronic disorder. A person can get acne at any age, whether they are a child or an adult. There are a number of factors contributing to acne, such as familial tendencies, acne bacteria, and hormones. A scattered part of the body's surface could also be the cause. This type of skin cancer is the most serious. During this process, melanocytes (pigment cells) grew uncontrollably [19]. It is very rare for melanoma to develop in children, but it can occur at any age. It is important to note that melanoma can have several colors, such as blue, brown, red, etc.

Long-term skin inflammation occurs when the skin becomes inflamed. At any age, men and women can suffer from it. Plaques with well-defined edges and symmetrical distribution of red color are characteristic of this disease.

EXPERIMENTAL RESULTS

This section presents a performance evaluation of the model. A variety of Python packages were used to implement the proposed model, namely Scikit-learn for machine learning algorithms, OpenCV, Glob, and OS for image processing, Skimage for filters, and Matplot for visualization. Spyder, an Anaconda environment, and several libraries were used as part of the implementation of the proposed model.

Measuring Evaluation

Several measures were used to analyze the model performance. As outlined below, there are four measures: (1), (2), (3), and (4).

Accuracy = (TP + TN) / (TP+FP+TN+FN) ....(1)
Precision = TP / (TP+FP) ....(2)

Recall = TP / (TP+FN)...(3)

F1-score = 2 * (precision * recall / precision + recall)........(4)

There are four types of positive tests: true positives, true negatives, false positives, and false negatives. To detect machine learning algorithms' behavior, data unrelated to the training process must be used to test the model. Datasets are divided into training and testing categories to accomplish this.

Results's comparison

As far as we know, no research has been conducted on diseases like those of this study. A comparison was made between the proposed model and research that examined some of the same diseases. The study lacked datasets due to a lack of available data. Images can be processed and classified using many techniques, and they have been used in the classification of several skin diseases. Moreover, studies have demonstrated that extraction techniques are crucial in extracting the features that are appropriate for classification.

Journal of Information Systems Engineering and Management
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https://www.jisem-journal.com/ **Research Article**

DISEASE CLASSIFICATION RATE

Classifiers	Diseases	Accuracy	Precision	Recall	F1-score
SVM	Actinic Keratosis	80%	80%	80%	85%
	Atopic Dermatitis	100%	90%	100%	99%
	Dermatofibroma	75%	79%	75%	77%
	Melanoma	90%	95%	90%	92%
K-NN	Actinic Keratosis	80%	42%	80%	55%
	Atopic Dermatitis	38%	80%	38%	52 %
	Dermatofibroma	75%	62%	75%	68%
	Melanoma	45%	100%	45%	62%
RF	Actinic Keratosis	85%	68%	85%	76%
	Atopic Dermatitis	90%	90%	90%	90%
	Dermatofibroma	70%	88%	70%	78%
	Melanoma	80%	84%	80%	82%

Table 2- Disease classifiers result

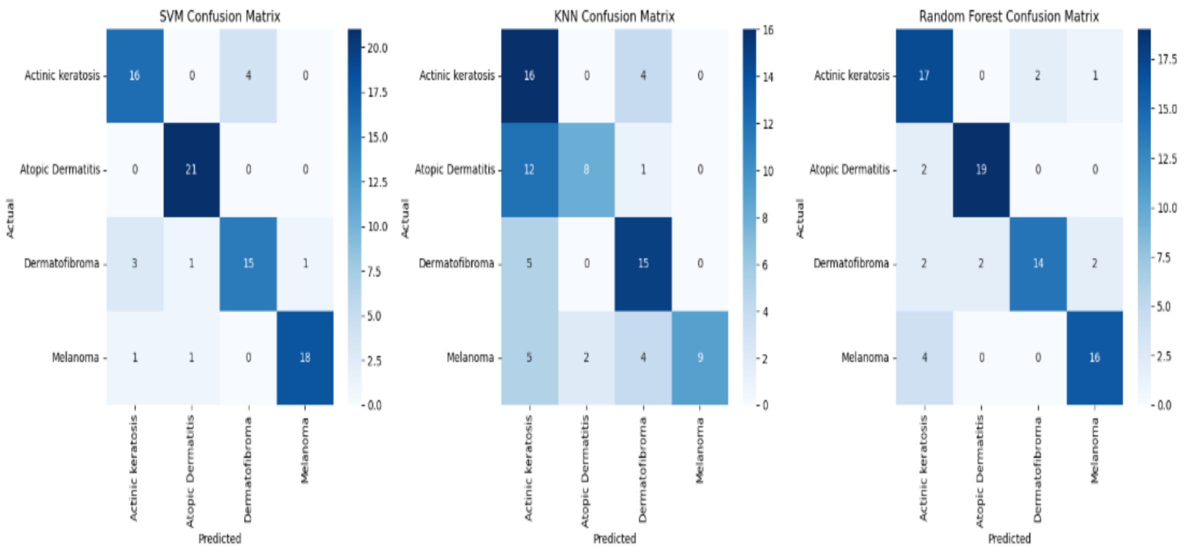

Fig 4- Confusion Matrix of SVM, RF and K-NN

Metrics in Table 2 are provided to show how well the three classifiers (SVM, RF, and K-NN) perform for different skin conditions, including Actinic Keratosis, Atopic Dermatitis, Dermatofibroma, and Melanoma. Figure 4 shows the confusion matrix of all the classifiers(SVM, RF and K-NN)The evaluation

Journal of Information Systems Engineering and Management
2024,9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

metrics include Accuracy, Precision, Recall, and F1-score. Here's a detailed explanation of the performance for each classifier:

Support Vector Machine (SVM):

1. **Actinic Keratosis:**
SVM achieves 80% accuracy, precision, and recall for Actinic Keratosis with a slightly higher F1-score of 85%, showing balanced performance.
2. **Atopic Dermatitis:**
For Atopic Dermatitis, SVM performs exceptionally well with 100% accuracy and recall, 90% precision, and an F1-score of 99%. This indicates near-perfect classification for this condition.
3. **Dermatofibroma:**
SVM achieves 75% accuracy and recall, 79% precision, and an F1-score of 77%. While the performance is decent, it's slightly less consistent compared to other conditions.
4. **Melanoma:**
SVM has 90% accuracy and recall, 95% precision, and a strong F1-score of 92%, reflecting reliable performance in identifying Melanoma.

Random Forest (RF):

1. **Actinic Keratosis:**
RF performs poorly for Actinic Keratosis with only 80% accuracy and recall, 42% precision, and an F1-score of 55%. The low precision indicates high false positives for this condition.
2. **Atopic Dermatitis:**
Atopic Dermatitis classification by RF has 38% accuracy and recall, 80% precision, and an F1-score of 52%, suggesting very inconsistent results.
3. **Dermatofibroma:**
RF shows balanced performance for Dermatofibroma with 75% accuracy and recall, 62% precision, and a moderate F1-score of 68%.
4. **Melanoma:**
For Melanoma, RF achieves 45% accuracy and recall, 100% precision, and an F1-score of 62%. While precision is perfect, low recall suggests many false negatives.

K-Nearest Neighbors (K-NN):

1. **Actinic Keratosis:**
K-NN performs well for Actinic Keratosis with 85% accuracy and recall, 68% precision, and an F1-score of 76%. The slightly lower precision indicates false positives.
2. **Atopic Dermatitis:**
For Atopic Dermatitis, K-NN achieves consistent results with 90% accuracy, precision, recall, and an F1-score of 90%, showing robust performance.
3. **Dermatofibroma:**
K-NN shows decent performance for Dermatofibroma with 70% accuracy and recall, 88% precision, and an F1-score of 78%. The higher precision compensates for slightly lower recall.
4. **Melanoma:**
For Melanoma, K-NN achieves 80% accuracy and recall, 84% precision, and an F1-score of 82%. This indicates reliable classification performance.

The SVM performs the best on all metrics and skin conditions in this dataset, making it the most effective classifier. The performance of RF is better than that of K-NN, but it varies depending on the

Journal of Information Systems Engineering and Management
2024,9(4s)
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https://www.jisem-journal.com/ **Research Article**

conditions. It appears that K-NN is not suitable for such a classification task, since it consistently underperforms.

CLASSIFIERS RESULTS

Classifier	Accuracy	Precision	Recall	F1-Score
SVM	86.41%	86.30%	86.41%	86.28%
RF	81.48%	82.64%	81.48%	81.57%
K-NN	59.25%	71.26%	59.25%	59.16%

Table 3- Classifiers Result

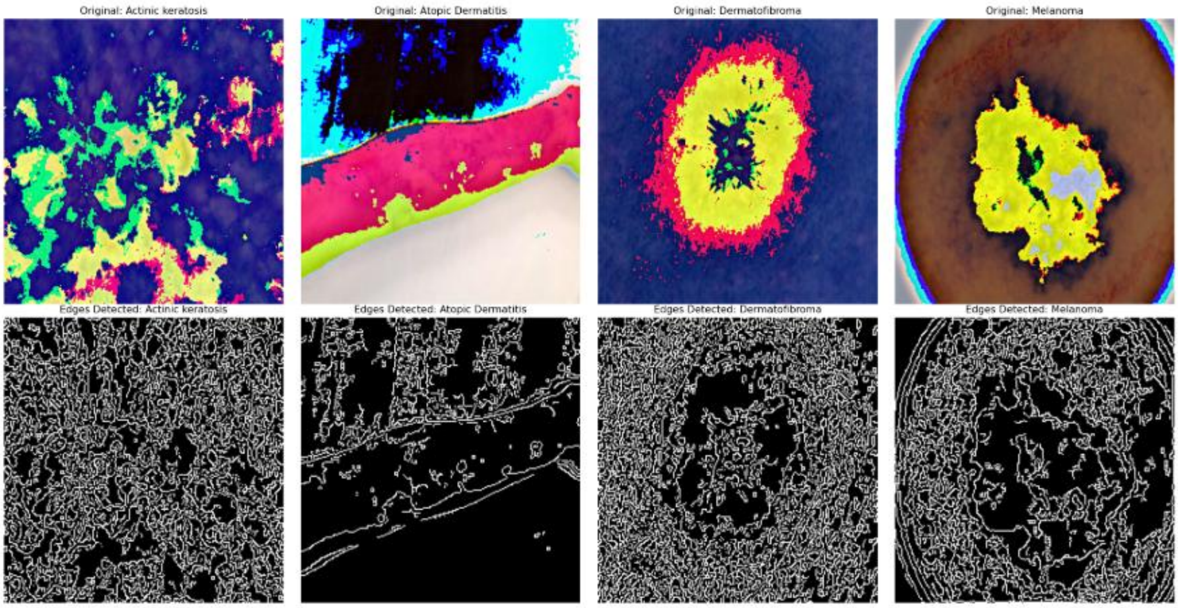

Fig 5- Disease Results

Based on the updated metrics provided in table 3, **SVM (Support Vector Machine)** leads the performance with an **accuracy of 86.41%**, followed by **RF (Random Forest)** at **81.48%**, and **K-NN (K-Nearest Neighbors)** with the lowest accuracy of **59.25%**. Figure 5 shows are results of all three different diseases.

In terms of **precision**, RF slightly outperforms SVM with **82.64%**, while SVM achieves **86.30%**, and K-NN trails with **71.26%**. For **recall**, SVM again takes the lead at **86.41%**, RF follows closely with **81.48%**, and K-NN lags behind at **59.25%**. Similarly, for the **F1-score**, SVM performs the best with **86.28%**, RF achieves **81.57%**, and K-NN has the lowest F1-score of **59.16%**.

There was a lack of available images for the diseases tested, which made developing the proposed model difficult. The literature also includes a few papers that discuss a variety of skin diseases. A model may also be better able to diagnose new images and select appropriate techniques to extract useful information from them in addition to training more images.

Journal of Information Systems Engineering and Management
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https://www.jisem-journal.com/ **Research Article**

CONCLUSION

Actinic Keratosis, Atopic Dermatitis, Dermatofibroma, and Melanoma are some of the skin diseases classified in this study. While most research in this area has focused on skin cancer, there is a lack of studies addressing these specific diseases. To address this gap, our model was developed using **402 images**, processed with machine learning and image processing algorithms. The dataset was divided into **321 training images** and **81 testing images**. The images were preprocessed by resizing, denoising using a median filter, converting to grayscale, segmenting the infected area using Otsu's method, and extracting features using Gabor, Entropy, and Sobel techniques.

In the second step, we evaluated the performance of three classifiers: **SVM, RF, and K-NN**, using metrics such as accuracy, precision, recall, and F1-score. The results show that **SVM performed the best, achieving an accuracy of 86.41%, precision of 86.30%, recall of 86.41%, and F1-score of 86.28%**. **RF** followed with an accuracy of 81.48%, precision of 82.64%, recall of 81.48%, and F1-score of 81.57%. **K-NN**, however, showed the weakest performance, with an accuracy of 59.25%, precision of 71.26%, recall of 59.25%, and F1-score of 59.16%. These findings highlight SVM as the most reliable classifier for this task.

In terms of disease-specific results:

- **SVM** demonstrated the highest accuracy for diseases such as Atopic Dermatitis (100%), Actinic Keratosis (80%), and Melanoma (90%).
- **RF** showed varying performance, with its best accuracy for Actinic Keratosis (80%), but struggled with Atopic Dermatitis and Melanoma.
- **K-NN** achieved moderate performance in Actinic Keratosis (85%) but failed to match SVM and RF in other diseases.

Overall, the proposed model's accuracy using SVM was higher than comparable studies, with the exception of one paper. The key challenge was sourcing a public dataset of skin disease images, as creating a local dataset was difficult. Expanding the dataset with more images could significantly improve the model's accuracy and generalizability. This research lays the foundation for developing applications that can quickly and easily diagnose these skin diseases on smartphones, making early detection and treatment more accessible.

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Data Availability Statement- NA

Research Involving Human and /or Animals- NA

Informed Consent- NA

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