A Fully Automated Image Mining Approach for Accurate Classification of Skin Disorders

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Abstract:

Skin disorders pose a significant diagnostic challenge due to their complex visual patterns and dependence on expert interpretation. Early and accurate diagnosis is essential to ensure effective treatment and to prevent the progression of skin-related diseases. This paper presents a fully automated skin disorder diagnosis system based on image mining techniques. The proposed framework follows a three-stage methodology comprising data augmentation, feature extraction, and classification. A dataset containing images of three common skin disorders—acne, cold sores, and hives—is developed and enhanced using augmentation techniques to improve classification performance. Image processing methods such as image conversion, sharpening, and edge detection are employed to extract discriminative features from the images. These features are then classified using a Support Vector Machine (SVM) classifier. Experimental results demonstrate that the proposed system achieves satisfactory classification accuracy with reasonable computational efficiency. The study confirms that image mining combined with machine learning techniques can effectively support early-stage diagnosis of skin disorders and assist in computer-aided dermatological decision-making.

Keywords:

Skin Disorders, Image Mining, Image Processing, Feature Extraction, Support Vector Machine (SVM), Image Classification, Computer-Aided Diagnosis

Introduction:

The skin is the largest and one of the most essential organs of the human body, comprising the epidermis, dermis, and subcutaneous tissues. It acts as a protective barrier between internal organs and the external environment while playing a vital role in sensory perception and immune defence [1]. Continuous exposure to environmental pollutants, chemicals, ultraviolet radiation, and microorganisms makes the skin vulnerable to a wide range of disorders. Skin disorders pose a serious medical challenge due to their complex diagnosis, which often requires expert interpretation and extensive clinical experience. Factors such as genetic abnormalities, immune system deficiencies, microbial infections, and negligence in personal skin care significantly contribute to the occurrence of dermatological diseases [2]. Common skin conditions such as acne, cold sores, and hives may appear minor at early stages but can spread rapidly and lead to severe complications if not diagnosed and treated promptly.

Conventional diagnosis of skin disorders primarily relies on subjective visual assessment by dermatologists. Although home remedies are frequently adopted for treating skin conditions, delayed or improper diagnosis may aggravate the disease and result in long-term health issues [3]. Moreover, the growing patient population and limited availability of dermatology specialists highlight the need for reliable automated diagnostic solutions.

Advancements in image processing, computer vision, and machine learning have enabled the development of computer-aided diagnostic systems for medical image analysis. Image mining techniques allow the extraction of meaningful patterns and discriminative features from skin images, facilitating effective classification and prediction of skin disorders [4]. Several studies have demonstrated that supervised learning approaches can significantly improve diagnostic accuracy and consistency compared to manual inspection [5].

In this paper, a fully automated image mining–based framework for skin disorder diagnosis is presented. The proposed system follows a three-stage methodology comprising data augmentation, feature extraction, and classification. A curated dataset containing images of acne, cold sores, and hives is developed and enhanced using augmentation techniques. Image processing methods such as sharpening and edge detection are applied to extract relevant features, which are subsequently classified using a Support Vector Machine (SVM) classifier. The proposed approach aims to support early-stage diagnosis of skin disorders with improved accuracy and reduced human intervention [6].

literature survey:

Automated skin disease diagnosis has gained significant attention in recent years due to advancements in image processing, machine learning, and deep learning techniques. Several researchers have proposed computer-aided diagnostic systems to improve the accuracy and efficiency of skin disorder identification.

Early studies focused on traditional image processing techniques combined with machine learning classifiers. In [1], a two-stage system was proposed for skin disease analysis using colour images. The first stage involved detecting infected skin regions using k-means clustering and colour gradient analysis, while the second stage employed artificial neural networks for disease classification. The system achieved promising accuracy, demonstrating the feasibility of automated diagnosis without direct physician involvement.

Feature extraction plays a critical role in improving classification performance. The authors in [2] highlighted that extracting a larger and more diverse set of image features significantly enhances diagnostic accuracy. Their approach was applied to nine different skin diseases and achieved an accuracy of up to 90%. Accurate feature representation is particularly important for detecting melanoma, a life-threatening skin cancer that requires early diagnosis.

Segmentation-based techniques have also been widely explored for precise lesion detection. In [3], various segmentation methods were analysed to accurately delineate melanoma-affected regions. Effective segmentation was shown to improve feature extraction and assist in reliable diagnosis. Similarly, a specialized algorithm and database were developed in [4] to address the challenges of melanoma detection in dark skin tones, emphasizing the importance of inclusive datasets.

Machine learning classifiers such as Support Vector Machines (SVMs) have demonstrated strong performance in skin disease classification. In [5], SVM-based classification was applied to distinguish between melanoma, basal cell carcinoma, nevus, and seborrheic keratosis. The study reported higher accuracy for SVM compared to other classifiers, validating its suitability for medical image classification tasks.

With the rise of deep learning, convolutional neural networks (CNNs) have been increasingly employed for skin disease diagnosis. Esteva *et al.* [6] demonstrated dermatologist-level performance in skin cancer classification using deep neural networks trained on large-scale image datasets. Several subsequent studies [7]–[10] further confirmed the effectiveness of deep learning models in recognizing complex skin disease patterns, although these approaches often require large labelled datasets and high computational resources.

Despite the success of deep learning-based methods, traditional image mining and machine learning approaches remain relevant due to their lower computational complexity and suitability for small and medium-sized datasets. Recent surveys [11], [12] emphasize that hybrid frameworks combining image processing, feature extraction, and classical classifiers can deliver reliable performance with reduced implementation complexity.

Based on the reviewed literature, it is evident that image mining techniques integrated with machine learning classifiers provide an effective solution for automated skin disorder diagnosis. However, challenges such as limited dataset availability, early-stage detection, and computational efficiency remain open research issues. Motivated by these observations, the present work proposes an image mining–based diagnostic framework focusing on early-stage identification of common skin disorders using an efficient SVM classifier.

Block Diagram:

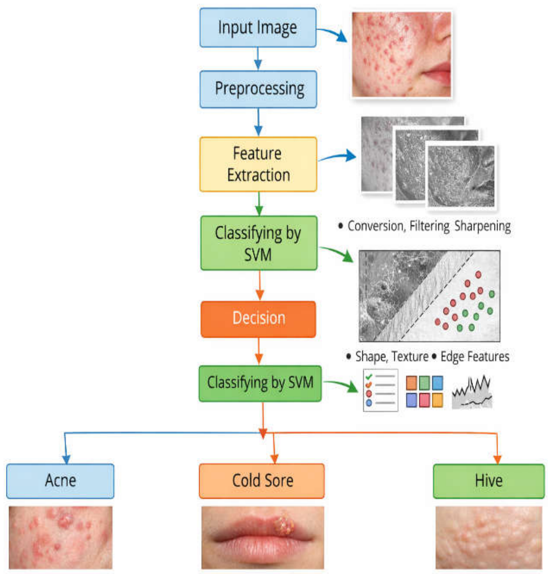


Fig.1: Block Diagram for Diagnosis Mechanism for Skin Disorders

The proposed block diagram represents an automated image mining–based system for the diagnosis of skin disorders. The process begins with the acquisition of an input skin image, which may correspond to conditions such as acne, cold sores, or hives. The acquired image is first subjected to pre-processing to enhance its quality and ensure uniformity across the dataset. This stage involves operations such as image resizing, colour space conversion, noise removal through filtering, and image sharpening to highlight important regions while suppressing irrelevant background information. The pre-processed image is then passed to the feature extraction stage, where significant visual characteristics such as edges, texture patterns, and shape-related features are extracted using image processing techniques. These features effectively capture the distinguishing patterns associated with different skin disorders and are represented in the form of numerical feature vectors. The extracted features are subsequently fed into a Support Vector Machine (SVM) classifier, which is trained using labelled skin disorder images to learn optimal decision boundaries between different classes. Based on the classification results produced by the SVM, the decision module determines the most probable skin disorder present in the input image. Finally, the system outputs the predicted class, categorizing the skin condition as acne, cold sore, or hive. This structured workflow enables accurate and efficient diagnosis of skin disorders and supports early-stage detection with minimal human intervention.

Table 1. Common Skin Disorders

Sl. No.	Skin Disorder	Key Features	Commonly Affected Areas
1	Acne	Pimples, blackheads, inflammation	Face, neck, shoulders, chest, upper back
2	Cold Sore	Red blisters, fluid-filled lesions	Lips, mouth corners
3	Hives	Red, swollen welts, itching	Arms, legs, torso
4	Eczema	Dry skin, redness, itching	Hands, face, elbows
5	Psoriasis	Thick scaly patches, silvery flakes	Scalp, knees, elbows
6	Ringworm	Circular rash with raised edges	Body, scalp, feet
7	Rosacea	Facial redness, visible blood vessels	Cheeks, nose
8	Impetigo	Honey-coloured crusts, sores	Face, hands
9	Vitiligo	Loss of skin pigmentation	Hands, face, joints
10	Melanoma	Irregular mole, colour variation	Sun-exposed areas

Table 1presents the common skin disorders considered in the proposed experimental study, namely Acne, Cold Sore, and Hives. These disorders were selected due to their high prevalence and distinct visual characteristics, which make them suitable for image-based classification. For each disorder, the table summarizes the key clinical features along with a representative sample image to provide visual understanding. Acne is characterized by the presence of pimples, blackheads, and inflammatory lesions, commonly occurring on the face, neck, shoulders, chest, and upper back. Cold sores are identified by red, fluid-filled blisters that usually appear around the lips and mouth area and are often painful. Hives are characterized by red, swollen welts on the skin, accompanied by itching and a warm sensation. The inclusion of sample images in the table helps illustrate the visual differences among the selected skin disorders, which are crucial for effective feature extraction and classification in the proposed image mining–based diagnosis system.

Table 2. Common Skin Disorders Used in the Experiment

Sl. No.	Skin Disorder	Key Features	Sample Image
1	Acne	Pimples, blackheads, inflammation, oily skin	

Sl. No.	Skin Disorder	Key Features	Sample Image
2	Cold Sore	Red, fluid-filled blisters, painful lesions	
3	Hives	Red swollen welts, itching, warmth	

Common Skin Disorders Used in the Experiment

Skin disorders constitute a major public health concern due to their increasing prevalence and the complexity involved in accurate diagnosis. Many dermatological conditions exhibit overlapping visual features such as redness, inflammation, and textural variations, which often makes manual diagnosis subjective and time-consuming. In order to develop an effective and reliable automated diagnostic system, it is essential to select skin disorders that are not only clinically significant but also exhibit visually distinguishable characteristics suitable for image-based analysis. Based on these considerations, the present experimental study focuses on three common skin disorders: acne, cold sore, and hives.

These disorders were chosen because they are frequently observed in clinical practice, affect individuals across different age groups, and present unique visual patterns in terms of colour, shape, texture, and lesion distribution. Moreover, early detection of these conditions plays a crucial role in preventing disease progression and reducing patient discomfort. The selected disorders provide an ideal testbed for evaluating the performance of the proposed image mining and Support Vector Machine (SVM)-based classification framework.

Acne

Acne is one of the most common chronic inflammatory skin disorders, predominantly affecting adolescents and young adults, although it can persist into later stages of life. It is primarily caused by the blockage of hair follicles due to excess oil production, dead skin cells, and bacterial activity. Clinically, acne manifests as pimples, blackheads, whiteheads, papules, pustules, nodules, or cysts. These lesions typically appear on the face, neck, shoulders, chest, and upper back, where sebaceous glands are highly concentrated.

From an image analysis perspective, acne lesions are characterized by distinct visual features such as localized redness, irregular shapes, elevated surfaces, and variations in skin texture. These properties make acne suitable for automated detection using image processing techniques. In the proposed system, pre-processing techniques enhance lesion visibility, while feature extraction methods capture textural and edge-based information that differentiates acne-affected regions from healthy skin. Including acne in the dataset allows the system to learn subtle variations in lesion appearance, which is essential for accurate classification and early diagnosis.

Cold Sore

Cold sores, also known as herpes labialis, are viral infections caused by the herpes simplex virus (HSV). They are highly contagious and commonly appear around the lips, mouth corners, and occasionally near the nose. Cold sores typically begin as red, inflamed areas that develop into small, fluid-filled blisters. These blisters may rupture, crust over, and heal within a few days, often accompanied by pain, itching, or a burning sensation.

In visual terms, cold sores exhibit strong colour contrast, distinct boundaries, and clustered lesion patterns, making them suitable for image-based recognition. The red coloration and glossy appearance of the blisters provide important cues for feature extraction. In the experimental framework, cold sore images help the classifier learn colour-based and shape-based features that distinguish viral lesions from other inflammatory skin conditions. Accurate classification of cold sores is particularly important because early diagnosis can help prevent viral spread and initiate timely treatment.

Hives

Hives, medically referred to as urticaria, are characterized by the sudden appearance of red, swollen welts on the skin. These welts often vary in size and shape and are commonly associated with itching, warmth, and irritation. Hives can occur due to allergic reactions, infections, stress, or environmental factors, and they may appear anywhere on the body, including the arms, legs, and torso.

Unlike acne and cold sores, hives do not typically form permanent lesions; instead, they appear and disappear within a short duration. Visually, hives are marked by raised skin surfaces, diffuse redness, and irregular boundaries. These features present a unique challenge for automated diagnosis, as the lesions may lack sharp edges and consistent patterns. By including hives in the experimental dataset, the proposed system is tested for its robustness in handling dynamically shaped and texture-based skin abnormalities. Feature extraction techniques focusing on edge detection and texture variation play a crucial role in distinguishing hives from other disorders.

Significance of Disorder Selection

The inclusion of acne, cold sore, and hives in the experiment ensures diversity in lesion appearance and underlying causes, ranging from inflammatory and viral to allergic conditions. This diversity enables comprehensive evaluation of the proposed image mining framework and enhances the generalizability of the classification model. Each disorder contributes unique visual patterns, allowing the SVM classifier to learn distinct decision boundaries based on extracted features.

Furthermore, limiting the experimental dataset to these three disorders allows focused analysis while maintaining manageable computational complexity. This approach is particularly suitable for early-stage research and for systems designed to operate in environments with limited computational resources. The use of representative sample images in the dataset also helps improve the robustness of the model by exposing it to variations in lighting conditions, skin tones, and lesion severity.

the experimental study employs three common skin disorders—acne, cold sore, and hives—to evaluate the effectiveness of the proposed automated diagnosis system. These disorders were selected due to their clinical relevance, prevalence, and visually distinguishable features. By analysing their unique characteristics through image pre-processing, feature extraction, and SVM-based classification, the proposed system demonstrates its capability to accurately identify and classify skin disorders. The focused selection of disorders ensures reliable performance assessment while laying the foundation for future extension of the system to include a broader range of dermatological conditions.

Different Methods Adopted:

Several research efforts have been carried out in the field of automated skin disorder diagnosis using image processing, machine learning, and deep learning techniques. The methodologies adopted in previous studies vary based on the type of skin disorder considered, dataset size, feature representation, and classification approach. This section discusses the major methods employed in earlier works.

Early research primarily focused on traditional image processing techniques combined with classical machine learning algorithms. In many studies, colour-based segmentation methods such as k-means clustering and thresholding were used to isolate infected skin regions from healthy skin. These approaches relied on colour gradients and pixel intensity variations to identify lesion boundaries, followed by classification using artificial neural networks (ANNs) or decision-based classifiers. Such systems demonstrated reasonable accuracy for a limited number of skin diseases but were sensitive to lighting conditions and image quality.

Feature extraction–based approaches have been widely adopted to improve diagnostic performance. Several authors emphasized extracting handcrafted features such as colour histograms, texture descriptors (GLCM, LBP), and shape features to represent skin lesions numerically. These features were then classified using machine learning algorithms including Support Vector Machines (SVM), k-Nearest Neighbour (kNN), and Decision Trees. Among these classifiers, SVM was frequently reported to achieve higher accuracy due to its ability to handle high-dimensional feature spaces and nonlinear decision boundaries.

Segmentation-driven methodologies have also been extensively explored, particularly for melanoma and other skin cancers. In these approaches, accurate segmentation of lesion boundaries was considered a crucial step prior to feature extraction. Techniques such as region growing, active contour models, and edge-based segmentation were employed to precisely isolate the affected regions. These segmented regions enabled improved feature extraction and enhanced classification accuracy, especially for irregular and asymmetrical lesions.

With the advancement of computational power and availability of large datasets, deep learning–based methods gained significant attention. Convolutional Neural Networks (CNNs) have been widely used to automatically learn hierarchical features from raw skin images without manual feature engineering. Several studies reported dermatologist-level performance using deep neural networks trained on large-scale dermo scope image datasets. Variants such as Mobile Net, ResNet, and hybrid CNN–LSTM models were also proposed to improve classification accuracy and reduce computational complexity.

Hybrid approaches combining image processing and deep learning have also been reported in the literature. In such methods, pre-processing and segmentation are first applied to enhance lesion visibility, followed by deep learning–based classification. Although these approaches achieved high accuracy, they often require large annotated datasets, high computational resources, and longer training times, making them less suitable for real-time or resource-constrained environments.

Recent survey papers highlight that while deep learning models offer superior performance, image mining combined with classical machine learning techniques remains effective for small and medium-sized datasets. These approaches offer advantages such as reduced complexity, interpretability, and faster execution. Consequently, many researchers continue to adopt feature extraction–based frameworks with classifiers such as SVM for early-stage skin disorder diagnosis.

In summary, previous research has adopted a wide range of methodologies including traditional image processing, feature-based machine learning, segmentation-driven analysis, and deep learning models. Each approach has its own strengths and limitations in terms of accuracy, complexity, and dataset requirements. Motivated by these studies, the present work adopts an image mining framework combined with SVM classification to achieve a balance between accuracy, computational efficiency, and suitability for early-stage skin disorder diagnosis.

Methodology Adopted:

The proposed skin disorder diagnosis system is developed using a systematic three-stage methodology. The aim of this framework is to accurately classify skin disorder images by integrating image mining techniques with machine learning. The three stages include dataset preparation and augmentation, feature extraction, and classification and prediction. Each stage is described in detail below.

Stage 1: Dataset Collection and Augmentation

In the first stage, a dataset of skin disorder images is compiled to form the foundation of the proposed system. Images representing three common skin disorders—acne, cold sores, and hives—are collected from various online medical sources and image repositories. The dataset is manually curated to ensure relevance, clarity, and correct labeling of each image class.

Initially, the dataset contains only 30 images, which is insufficient for effective training of a machine learning model. To address this limitation and improve the robustness of the classifier, data augmentation techniques are applied. Augmentation methods such as Synthetic Minority Over-Sampling Technique (SMOTE) and perspective view transformation are used to artificially generate new images from the existing dataset. These techniques introduce variations in orientation and viewpoint while preserving the original characteristics of the skin disorder. As a result, the dataset size is increased from 30 to 150 images, reducing class imbalance and enhancing the generalization capability of the model.

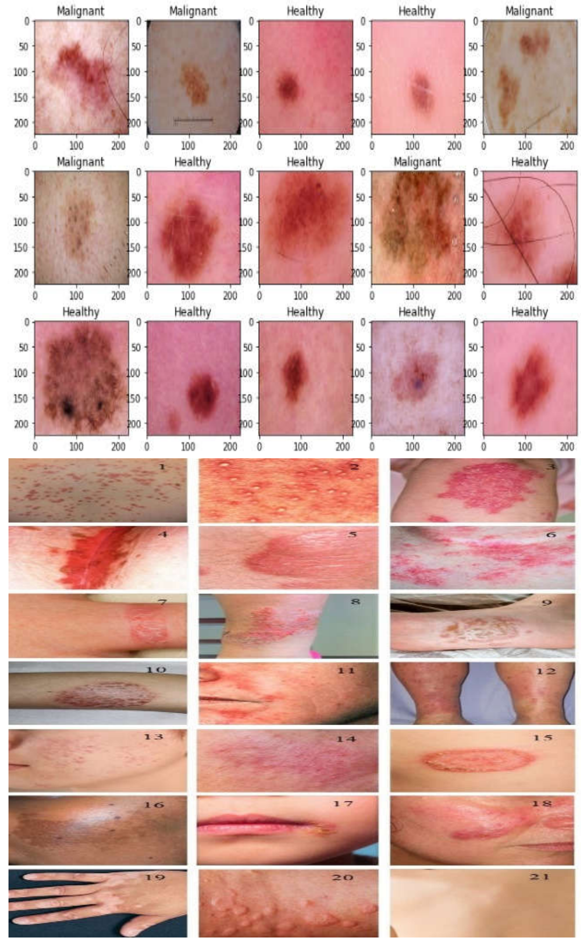
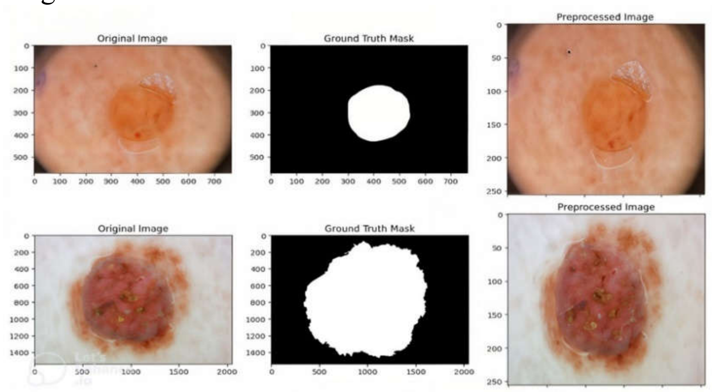


Fig. 2. Dataset collection and augmentation process

Stage 2: Feature Extraction



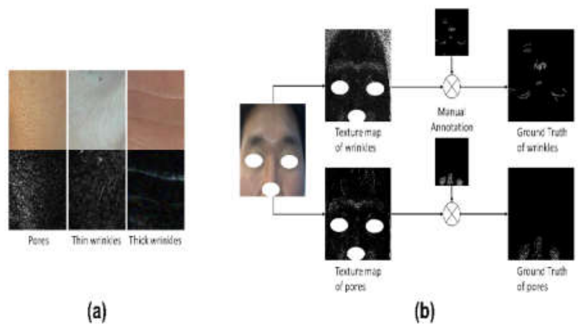


Fig. 3. Feature extraction stages for skin disorder images

The second stage focuses on extracting discriminative features from the skin disorder images. Before feature extraction, pre-processing operations are performed to enhance image quality and remove unwanted noise. These operations include image resizing, colour space conversion, filtering, and sharpening. Pre-processing ensures uniformity across the dataset and improves the visibility of lesion regions.

Once pre-processing is completed, various image processing techniques are applied to extract meaningful features. Edge detection methods are used to identify lesion boundaries, while texture analysis captures surface variations and patterns present in the affected skin regions. Shape-related features help in differentiating between clustered lesions, blisters, and irregular welts. These extracted attributes collectively represent the visual characteristics of each skin disorder. The features are then converted into numerical feature vectors, which serve as input to the classification stage.

Stage 3: Classification and Prediction

In the third stage, the extracted feature vectors are classified using a Support Vector Machine (SVM) classifier. SVM is a supervised machine learning algorithm widely used for classification tasks due to its ability to handle high-dimensional data and its strong generalization performance. The classifier is trained using the augmented dataset, where each feature vector is labelled according to its corresponding skin disorder class.

During the training process, the SVM learns optimal decision boundaries that separate the feature space into distinct regions corresponding to acne, cold sores, and hives. Once trained, the model is tested using unseen images. The trained SVM analyses the extracted features and predicts the most probable skin disorder class. The final decision is generated based on the classifier output, and the system displays the predicted skin disorder as the output.

The proposed methodology integrates image mining and machine learning techniques into a unified framework. By combining dataset augmentation, effective feature extraction, and SVM-based classification, the system achieves accurate and efficient diagnosis of skin disorders. The structured three-stage approach ensures scalability, robustness, and suitability for early-stage skin disorder detection.

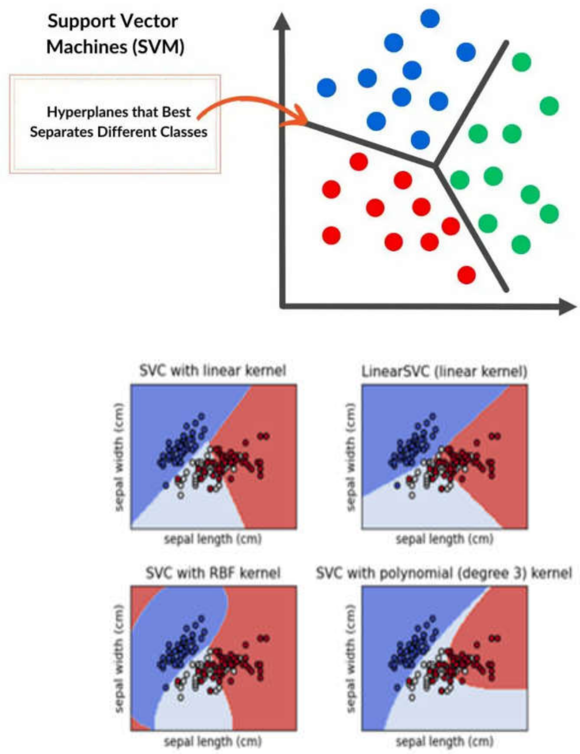


Fig. 4. SVM-based classification and prediction framework

Mathematical Formulation of Support Vector Machine (SVM):

Support Vector Machine (SVM) is a supervised learning algorithm widely used for classification tasks due to its ability to handle high-dimensional feature spaces and achieve strong generalization performance. In the proposed system, SVM is employed to classify skin disorder images based on the extracted feature vectors.

Let the training dataset be represented as

$$\{(x_i, y_i)\}_{i=1}^{N},$$

where $x_i \in \mathbb{R}^d$ denotes the d-dimensional feature vector extracted from the i^{th} skin disorder image, and $y_i \in \{-1, +1\}$ represents the corresponding class label.

Linear SVM

For linearly separable data, the objective of SVM is to find an optimal hyperplane defined by

$$w \cdot x + b = 0,$$

where www is the weight vector and b is the bias term. The optimal hyperplane maximizes the margin between the two classes.

The margin maximization problem can be formulated as:

$$\min_{w,b} \frac{1}{2}\|w\|^2$$

subject to

$$y_i(w \cdot x_i + b) \geq 1, \quad i = 1, 2, \ldots, N.$$

In practical applications such as skin disorder classification, the data may not be perfectly separable. To handle misclassification, slack variables ξi are introduced, resulting in the soft margin SVM formulation:

$$\min_{w,b,\xi} \left(\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N} \xi_i \right)$$

subject to

$$y_i(w \cdot x_i + b) \geq 1 - \xi_i, \quad \xi_i \geq 0,$$

where C is a regularization parameter that controls the trade-off between margin maximization and classification error.

Kernel-Based SVM

To handle non-linear separability, SVM employs kernel functions that map the input data into a higher-dimensional feature space. The decision function is expressed as:

$$f(x) = \sum_{i=1}^{N} \alpha_i y_i K(x_i, x) + b,$$

where α_i are Lagrange multipliers and $K(x_i, x)$ is the kernel function.

In the proposed skin disorder diagnosis system, the extracted image features serve as input vectors to the SVM classifier. The SVM model learns optimal decision boundaries that separate different skin disorder classes with maximum margin. This mathematical formulation ensures robust classification performance and effective generalization for unseen skin disorder images.

Pre-Processing and SVM-Based Classification Framework for Automated Skin Disorder Diagnosis:

Pre-processing plays a crucial role in enhancing the effectiveness of the proposed skin disorder diagnosis model by improving data quality, expanding the dataset, and optimizing feature representation. Initially, the dataset consists of approximately 30 skin disorder images categorized into three classes, namely acne, cold sores, and hives. Each image in the dataset exhibits distinct characteristics such as colour, shape, texture, and affected body region. To overcome the limitation of a small dataset and to improve model generalization, data augmentation techniques such as Synthetic Minority Over-Sampling Technique (SMOTE) and changes in perspective view are applied, thereby increasing the dataset size and reducing class imbalance. Following dataset preparation, meaningful features are extracted from the skin disorder images using various image processing techniques. Each image undergoes conversion, sharpening filtration, and edge detection to enhance important visual patterns and lesion boundaries that differentiate one skin disorder from another. The extracted features are then utilized in the classification stage, where image mining techniques are employed to categorize the images using different classification algorithms such as Support Vector Machine (SVM), Decision Trees, and k-Nearest Neighbour (kNN). Among these, SVM is selected in the proposed model due to its superior performance in handling high-dimensional feature spaces and its strong generalization capability. Finally, the trained SVM model predicts the type of skin disorder present in the input images by analysing the extracted features, resulting in accurate classification of acne, cold sores, and hives. By systematically integrating pre-processing, feature extraction, classification, and prediction, the proposed model demonstrates effective and reliable performance in automated skin disorder diagnosis.

Results & Discussion:

Testbed Environment

The experiments were conducted on a system equipped with an Intel Celeron J1900 processor operating at 1.99 GHz, 4 GB RAM, and running on 64-bit Windows 10 Ultimate. The implementation and testing of the proposed skin disorder diagnosis system were carried out using Python-based software development and scripting tools.

Dataset Description

The performance of the proposed approach was evaluated using a dataset comprising 150 skin disorder images. All images are 8-bit RGB images with a resolution of 768 × 560 pixels. The dataset includes images of three common skin disorders: Acne, Cold Sore, and Hives, with 50 images per class.

Classification Results

Table 3. Skin Disorder Classification Results Using SVM

Sl. No.	Skin Disorder	Total Images	Disorder Classified	Classification Rate
1	Acne	50	47	94%
2	Cold Sore	50	46	92%
3	Hives	50	49	98%

Table 4. Skin Disorder Classification Results Using Decision Tree

Sl. No.	Skin Disorder	Total Images	Disorder Classified	Classification Rate
1	Acne	50	44	88%
2	Cold Sore	50	46	92%
3	Hives	50	42	84%

Table 5. Skin Disorder Classification Results Using kNN

Sl. No.	Skin Disorder	Total Images	Disorder Classified	Classification Rate
1	Acne	50	45	90%
2	Cold Sore	50	43	86%
3	Hives	50	40	80%

The performance of the proposed skin disorder diagnosis system was evaluated primarily using classification accuracy as the key metric. A total of 150 RGB images were processed during experimentation, and the overall diagnosis process required approximately 1380 seconds, resulting in an average processing time of 9.65 seconds per image. This demonstrates the computational feasibility of the proposed framework for practical diagnostic applications.
From Table 3, it is observed that the Support Vector Machine (SVM) classifier achieved the highest classification accuracy across all three skin disorders. In particular, SVM attained 94% accuracy for acne, 92% for cold sore, and 98% for hives, indicating its strong capability in handling high-dimensional feature spaces and effectively separating different skin disorder classes.
The Decision Tree classifier, as shown in Table 4, exhibited moderate performance, achieving classification rates of 88%, 92%, and 84% for acne, cold sore, and hives respectively. Although Decision Trees offer interpretability and fast training, their performance is comparatively lower due to sensitivity to feature variations.
The k-Nearest Neighbour (kNN) classifier results are presented in Table 5. The accuracy obtained using kNN is 90% for acne, 86% for cold sore, and 80% for hives. The reduced performance of kNN can be attributed to its dependency on distance measures and sensitivity to noise in feature space.
Overall, the experimental results clearly indicate that the SVM-based classification approach outperforms Decision Tree and kNN classifiers in terms of accuracy and reliability. The combination of effective pre-processing, robust feature extraction, and SVM-based classification enables accurate and efficient diagnosis of skin disorders. These results validate the effectiveness of the proposed image mining framework and highlight its potential for early-stage automated skin disorder diagnosis.

Accuracy Comparison Graph:
The following graph illustrates the average classification accuracy comparison among the three classifiers used in the experiment.

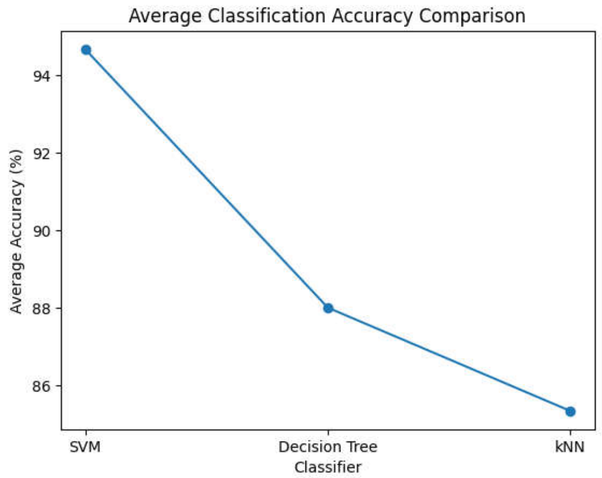


Fig.5: Average Classification Accuracy Comparison

From the computed results and the accuracy comparison graph, it is evident that the Support Vector Machine (SVM) classifier outperforms the other classifiers with an overall average accuracy of 94.67%**.** This superior performance is attributed to SVM's ability to effectively handle high-dimensional feature spaces and construct optimal decision boundaries. The Decision Tree classifier achieves a moderate average accuracy of 88%, while the kNN classifier records the lowest performance at 85.33%**,** primarily due to its sensitivity to noise and dependence on distance metrics. The comparative analysis clearly demonstrates that the SVM-based approach provides the most reliable and accurate classification for the proposed skin disorder diagnosis system.

Conclusion:
In this paper, a fully automated image mining–based framework for the diagnosis of skin disorders has been presented. The proposed system focuses on the early-stage identification of three common skin disorders, namely acne, cold sores, and hives, using image processing and machine learning techniques. A structured three-stage methodology comprising dataset augmentation, feature extraction, and

classification was adopted to enhance diagnostic accuracy and robustness. Image pre-processing techniques such as image conversion, filtering, sharpening, and edge detection were employed to extract discriminative visual features from skin images. These features were subsequently classified using a Support Vector Machine (SVM) classifier.

Experimental evaluation was carried out using a dataset of 150 RGB images, and the performance of the proposed system was analysed using accuracy as the primary metric. Comparative analysis with Decision Tree and k-Nearest Neighbour classifiers demonstrated that the SVM-based approach achieved superior classification performance, with an overall average accuracy of 94.67%. The results confirm that the integration of image mining techniques with SVM classification provides an effective and computationally efficient solution for automated skin disorder diagnosis. The proposed system reduces reliance on subjective clinical judgment and can serve as a supportive tool for dermatologists in early and accurate diagnosis.

Future Scope Using Artificial Intelligence

The rapid advancement of artificial intelligence (AI) offers significant opportunities to further enhance the effectiveness, accuracy, and scalability of automated skin disorder diagnosis systems. One important future direction involves the integration of deep learning models, particularly convolutional neural networks (CNNs), to enable automatic feature learning directly from raw skin images. Unlike traditional feature extraction methods, CNNs can learn hierarchical and complex visual representations, which may improve diagnostic accuracy for subtle and early-stage skin disorders.

Another promising area is the adoption of transfer learning, where pre-trained deep learning models such as Res Net, Efficient Net, or Mobile Net can be fine-tuned using dermatological datasets. This approach can significantly reduce training time and improve performance, especially when labelled medical image datasets are limited. Additionally, hybrid models that combine handcrafted features with deep learning features may provide a balanced solution with improved interpretability and robustness.

The future scope also includes the application of AI-driven data augmentation and generative models, such as Generative Adversarial Networks (GANs), to create realistic synthetic skin disorder images. This can help address class imbalance and enhance the diversity of training data, leading to better generalization of the diagnostic system. Furthermore, explainable AI (XAI) techniques can be incorporated to provide visual explanations, such as heatmaps or attention maps, which highlight affected regions and improve clinician trust in AI-based decisions.

Integration of the proposed system into mobile and web-based platforms using AI-powered inference engines can enable real-time and remote skin disorder diagnosis, making dermatological care more accessible, particularly in rural and underserved regions. AI models can also be extended to perform severity assessment and progression analysis, assisting clinicians in treatment planning and monitoring disease evolution over time.

Finally, future research may focus on combining image-based AI models with clinical metadata, including patient history, age, and symptoms, to develop multimodal AI systems. Such systems can deliver personalized and more accurate diagnostic outcomes. With continuous advancements in AI algorithms and computational resources, these enhancements can transform automated skin disorder diagnosis into a comprehensive, intelligent, and clinically reliable decision-support system.

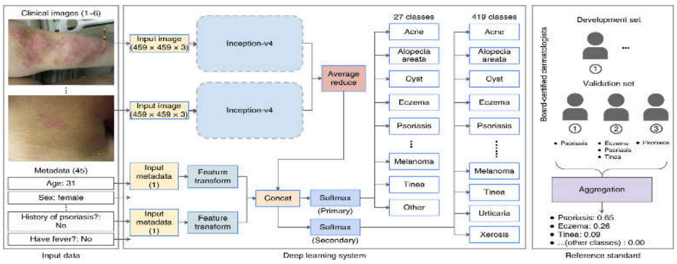


Fig. 6 Future AI-based framework for intelligent skin disorder diagnosis

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