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Emerging Trends in Clinical and Medical Science: Transforming Healthcare

Advanced skin disease detection: Image processing and modified genetic optimization with supervised k-nearest neighbors

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Abstract The use of modern technology to improve skin disease diagnosis includes things like artificial intelligence (AL), deep learning (DL) and computer vision. Medical images of skin lesions, dermatoscopic images, or thermal imaging can be analyzed by automated algorithms and image processing techniques to diagnose skin diseases. Diseases can cause physical and emotional suffering, making them silent killers. Extreme instances might cause skin cancer. skin disease diagnosis from clinical photographs is a key medical image processing challenge. Manual skin diagnosis takes time and it is subjective for doctors. Computerized skin disease prediction can simplify patient and dermatologist treatment planning. To tackle these issues, we proposed a genetic optimization and supervised K-Nearest Neighbor (MGO-SKNN) technique for detecting advanced skin diseases. The research gathers clinical data for detecting advanced skin diseases. Three methods were used to preprocess our data: noise reduction, hair removal and image resizing. The Grey Level Co-Occurrence Matrix (GLCM) approach was used in this work to extract features. The integration of image processing into MGO-SKNN represents a significant step forward in the quest for accurate, efficient and cutting-edge skin disease diagnosis. The metrics like accuracy (97.53%), precision (95.20%), recall (96.74%) and f1-score (98.06%) of our suggested technique, MGO-SKNN, exceed the traditional approaches for skin detection.

Keywords: image resizing, hair removal, grey level co-occurrence matrix (GLCM), deep learning (DL), noise removal, artificial intelligence (AI).

1. Introduction

The human skin exhibits varying thickness across different body regions, with the palms having the thickest and the soles among the thinnest. Comprising two primary layers, the outer epidermis and the inner dermis, the skin's remarkable pliability is attributed to its collagen and elastic components (Vestita and Tedeschi, 2022). However, the skin's vulnerability to mechanical stressors and chemical agents plays a pivotal role in developing dermatological conditions such as rosacea, acne and psoriasis. Consequently, dermatology has evolved into a competitive and compelling academic discipline, with a pressing need for innovative diagnostic approaches to reduce errors and facilitate early detection in remote areas with limited access to medical care (Berg et al., 2021).In the quest for accurate diagnosis, preprocessing of input images to eliminate noise and address image distortion is indispensable. After applying filters, images are converted to black and white,yet texture analysis is employed to generate thedescribed GLCM elements (Devunooru et al., 2021). Those images are categorized by employing a Support Vector Machine (SVM) classifier (Pedersen et al., 2022). The method holds significant potential for detecting psoriasis and other skin conditions through photographic analysis that is implemented using a MATLAB-based image processing technique (Malik et al., 2023). Due to the lack of public access to a comprehensive dataset, the study compiles images from diverse online sources for training and testing. The classifier's capabilities are improved by harnessing datasets encompassing a range of skin disorders, including acne, psoriasis, melanoma and rosacea. A collection of 105 images featuring various dermatological conditions, such as melanoma, rosacea and psoriasis, is assembled for training and testing (Jeong et al., 2023). To ensure image accuracy and focus, filtering techniques are employed to eliminate distracting backgrounds and extraneous elements, including adaptive median filtering for hair removal and thresholding for segmentation. The successful classification of skin images depicting different disorders relies on the intricate feature extraction methods that are applied in the approach (McHaney et al., 2021).

Kshirsagar et al. (2022) developed the fundamental objective of the system, which used MobileNetV2 and LSTM to develop taxonomies for skin disorders to deliver reliable skin disease predictions while requiring storage space. Goceri (2021) provided an entirely new model built using MobileNet, along with implementing a novel loss function. Three significant advances were made in the research: (i) The authors presented a unique hybrid loss function, (ii) Since the implementation of the new MobileNet architecture and (iii) a mobile phone application has been designed and implemented using the streamlined and designed MobileNet that has been tweaked. Jain et al. (2021) involving 20 general practitioners (GPs) and 20 nurse practitioners (NPs) analyzing 1048 retrospective cases, the application of AI demonstrated a significant improvement in consistency with the prognoses of a dermatological board. For GPs, the agreement increased from 48% to 58%, while for NPs, it increased from 46% to 58%. These findings suggest that the AI-driven approach would benefit approximately one case in every eight to ten. Kora et al. (2022) investigated the potential for automating the processing of medical images by utilizing Transfer Learning (TL) architectures. Their research uncovered various applications of TL in medical imaging, including segmentation, object identification, illness categorization and severity rating. Kumar et al. (2022) provided a thorough examination of the application of AI to the diagnosis of several ailments, such as Alzheimer's disease, cancer, diabetes, chronic heart disease, tuberculosis, stroke, cerebrovascular disease, hypertension, issues in skin and liver, as well as blood pressure issues, with a particular emphasis on medical imaging datasets, yet the methods used to extract and categorize features for predictive purposes. Liu et al. (2021) gathered the most up-to-date data on the development of DL research and its potential uses in clinical settings like medical imaging. Suggestions for overcoming these problems in the industry were provided. It's worth noting that the study summarized recent progress made using approaches based on convolutional neural networks in clinical settings. Gupta and Panwar (2021) offered a dataset with several preprocessed images of benign and malignant tumors. The images have been processed in preparation for feeding several CNN models. These models use visual data to train several machine learning (ML) classifiers on the signs of mole cancer. Iqbal et al. (2021) provided a DL model for automated categorization of multi-classes. To enhance efficiency and performance, the authors introduced a Reduced filters and parameters, many layers, and tunable filter sizes characterize the Deep Convolutional Neural Network (DCNN) model. The study used an archive of dermoscopy images for training and evaluation. Ahsan and Luna (2022) presented an in-depth review of developments in utilizing ML for early disease detection. The study commences with a bibliometric psychoanalysis utilizing Scopus and Web of Science (WOS) data, which involves examining 1216 publications to pinpoint the field's cited authors, nations and organizations. Saeed and Zeebaree (2021) offered an in-depth examination of current strategies for employing DLin identifying and categorizing skin cancer. Alam et al. (2022) presented a DL skin disease detector designed for an unbalanced dataset. Data augmentation techniques were applied to address the imbalance issue and close the gap in skin cancer categorization. The study focused on utilizing the seven distinct skin lesions from the HAM10000 dataset, demonstrating the application of DL in diagnosing visual diseases.

1.1. Our contributions

- The research collects clinical data. The data was preprocessed using noise reduction, hair removal and image scaling.
- We used three methods to preprocess our data: Noise removal, hair removal, and image resizing.
- We used the GLCM approach to extract features in this research.
- For the purpose of identifying advanced skin illnesses, we provided the MGO-SKNN approach.

The study's surviving parts are, A methodology is presented in part 2. Results and discussion are discussed in part 3 and part 4 represents the conclusions.

2. Materials and Methods

This work presents genetic optimization and image processing using MGO-SKNN. A patient can doubt skin-disease detection software. Healthcare patients naturally worry about AI accuracy. High-quality, diversified datasets are complex because real-world images differ in lighting, resolution and clarity. Patient care requires system integration with EHRs, medical databases and clinical data. MGO-SKNN was recommended to enhance skin condition recognition to overcome these issues. The research detects advanced skin disorders using clinical data. We preprocessed the data using noise reduction, hair removal and image scaling. Features were extracted using GLCM. Figure 1 depicts the outline of the research.

2.1. Data gathering

The research included a statistics database on 359 diseases and injuries worldwide from 1990 to 2017 and 84 risk factors. Location, age and gender can be used to further examine patterns and trends. To research trends and shifts in people's health, consult this interactive resource. Use the maps, arrow diagrams and other charts provided by this resource to analyze the trends efficiency. The outcomes are further dissected, down to the province level, for several countries. The map depicts the estimation at the state and provincial levels. Get access to contextual details about that region by selecting a region on the map or a pinpoint in the sky above the map legend. The tool's complex settings make it possible to get tailored rates for different ages (Kavita and Thakur, 2023).

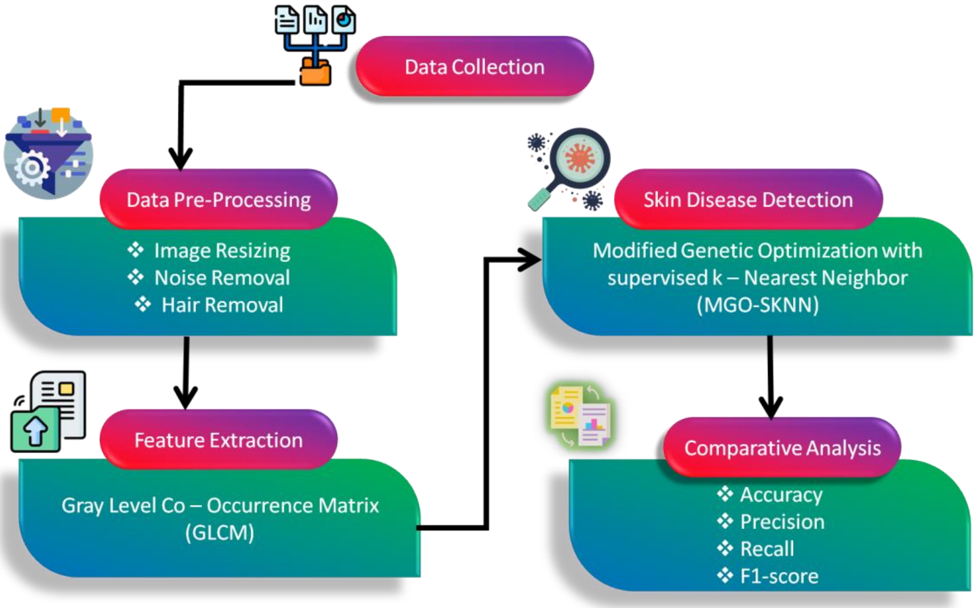

Figure 1 Outline of the research.

2.2. Data preprocessing

This study employed three preprocessing techniques: noise reduction, hair removal and image resizing. A preprocessed image has been modified before use. Photographs of the human skin have issues such as stray hairs, noise and distortion. An image processing system's output quality is directly proportional to the quality of the images it receives as input. Skin image processing is crucial to a reliable skin disease diagnosis system. It improves image quality, speeds up the process and makes the following processes precise. Image scaling, hair removal and noise reduction are a few operations in the preprocessing Stage.

2.2.1. Image Resizing

Attributes are sometimes handled differently for images of varying sizes. Therefore, the input images are scaled up or down to address this problem. As a result, the system processing time has decreased and its overall efficiency has improved. For this purpose, we reduced the size of input images to 512 pixels into 512 pixels. The original image is shown in Figure 2 (a) Before and 2(b) after resizing.

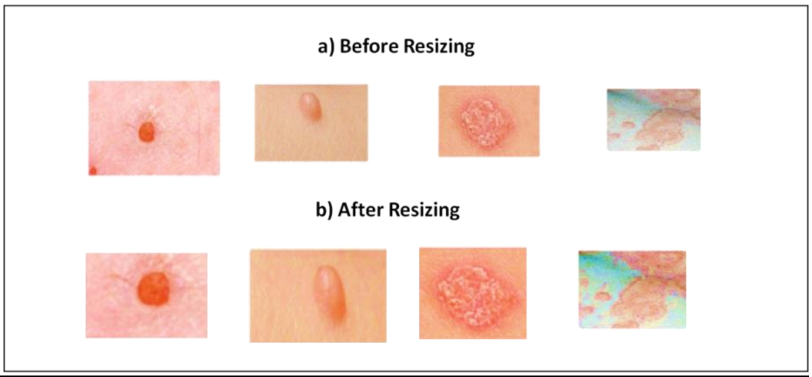

Figure 2 Before and After (a-b) Image Resizing. Source: https://abrir.link/sflXP

2.2.2. Noise Removal

Digital images are susceptible to noise throughout any processing phase, from capture to transmission to display. Rapid, unexpected shifts in brightness or color information can detract from the quality of an image. Standard image smoothing and noise removal filters include bilateral filtering, Gaussian blurring, mean blurring and median blurring. This system uses Gaussian filtering to clean up the photographs and make them seem more professional. To perform convolutional operations on the images, it employs a custom kernel. Equation (1) shows that the kernel values follow a Gaussian distribution. Figure 3 shows a) before the Gaussian filter and b) after the Gaussian filter.

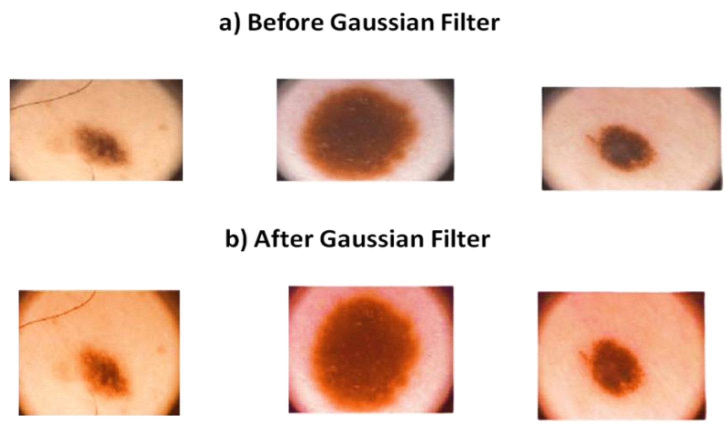

Figure 3 Before and after (a-b) using Gaussian filtered image. Source: https://abrir.link/OmsJv

$$S(y) = \frac{1}{\sqrt{2\pi\sigma^2}} a^{\frac{(y-\mu)^2}{2\sigma^2}} \qquad (1)$$

If we assume a normal distribution, then the mean is the standard deviation. The sigma value was calculated using a kernel of degree 77.

2.2.3. Hair Removal

De-hairing image can aid in the detection of skin diseases. Several methods, such as median filtering, Morphological, Gabor, PDE-based Inpainting and Adaptive Thresholding processes, have been applied to images of hairy skin. Figure 4 depicts a) before and b) after hair removal.In our suggested system, we employed the Black-Hat transformation and the in-painting methods are two examples of morphological filters that execute digital hair removal (DHR). The stages of this DHR algorithm are as follows:

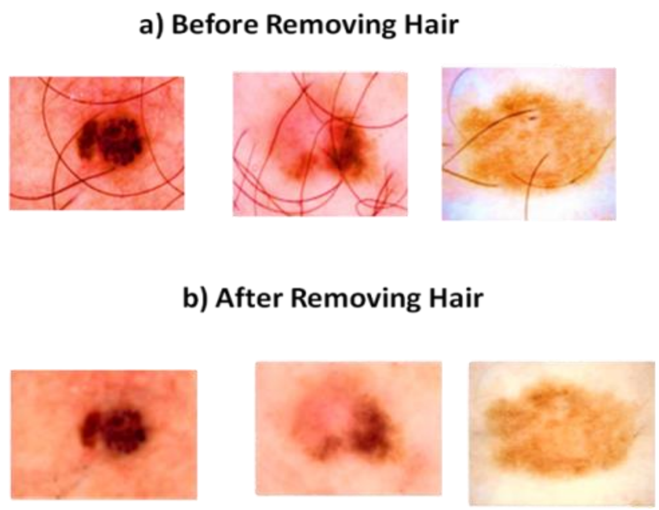

Figure 4 Before and after (a-b) hair removal image processing. Source: https://abrir.link/KqoGv

- Grayscale images can be created from RGB images.
- Edit the black-and-white images with the Morphological Black-Hat filter.
- Prepare an in-painting mask.
- This mask is used to paint the first version of the picture.

2.3. Feature extraction using Grey Level Co-Occurrence Matrix (GLCM)

This GarlickGLCM facilitates feature extraction from images by mapping the gray level co-occurrence probabilities using the spatial relations of pixels in various angular orientations. The angular second moment (energy), contrast, correlation, variance, inverse difference moment (homogeneity) and many other statistics can be derived from GLCM, including the mean, standard deviation, entropy, information measure of correlation and maximal correlation coefficient. Table 1 shows the different features of GCLM.

Table 1 Different types of GLCM features.

Name	Equation	Definition
Homogeneity	$\sum_{j,i=0}^{N-1} \frac{B_{ji}}{1+(j-i)^2}$	In the GLCM, Distributed component closeness is homogeneity.
Energy	$\sum_{\mathrm{j,i=0}}^{\mathrm{M-1}} (\mathrm{B_{ji}})^2$	It generates the GLCM's squared component sum between 0 and 1.
Contrast	$\sum_{j,i=0}^{N-1} B_{ji}(j-i)^2$	It is the degree to which pixels are related to one another generally.
Correlation	$\sum_{j,i=0}^{N-1} B_{ji} \frac{(j-\mu)(i-\mu)}{\sigma^2}$	It provides a gauge of how closely interconnected an image's pixels are.
Entropy	$\sum_{j,i=0}^{N-1} -In(B_{ji})\, B_{ji}$	The degree to which an image's pixels are consistent with one another and random is quantified by its entropy.

2.4. Modified Genetic Optimization (MGO)

Professor Holland was the one who presented the idea of MGO. Natural selection and the genetics of living things inspire this kind of randomized search algorithm. The finest individuals are picked from a pool of solutions kept alive between iterations to model natural processes like reproduction, crossover and mutation. Until the convergence index is met, genetic operators will combine the individuals to generate a new generation of solutions.The building blocks of an MGOinclude an encoding mechanism, a fitness function, genetic operators and a set of governing parameters. Participants of an MGO are informed on both the nature of the issue at present as well as the possible solutions to it. At first, a few people will attempt to resolve the problems. Terminated individuals and the estimated fitness function are output and the process is complete. A new population forms when individuals are allowed to mate with one another and undergo natural selection. The characteristics that have helped a population thrive in the past are passed on to the next generation and even more refined.This initial section has shown that MGO can be used for various optimization issues involving complex systems. In order to work, the MGOneeds the fitness function. In an iterative process, genetic operation reorganizes the population's structure. The following are brief explanations of a few primary forms of MGO. The following list outlines the processes of an MGOin algorithm 1.

Algorithm 1: Modified Genetic Optimization (MGO)

$SGA = (V, A, B_0, M, \Phi, \Gamma, \psi, D)$

V *- Separate Coding Procedures*

A *- Method for Judging Physical Condition*

B_0*- Population at the start*

M *- Quantity of people*

Φ *- Operator for selection*

Γ *- Operator for crossover*

ψ *- Operator for mutation*

D *- Prerequisite for genetic operation's termination*

1. Coding and creating the first population Next, create an initial population of M *individuals with identically sized chromosomes.*

$pop_j(d), d = 1, j = 1,2, \ldots, M$ *(2)*

2. Fitness value calculation: The fitnessor$pop_j(d)$ *of every chromosome in the population is calculated.*

$l_j = fitness(pop_j(d))$ *(2)*

Find out whether the requirement for convergence has been met. We will proceed to the next phase if the search returns relevant results.

3. Operator for selection

The fitness levels of applicants are taken into account while making selections: Their particular fitness determines each person's odds of being chosen.

$B_j = \frac{l_j}{\sum_{j=1}^{M} l_j}, j = 1,2,3, \ldots, M$ *(3)*

$newpop(d+1) = \{pop_i(d) | i = 1,2, \ldots, M\}$ *(3)*

4. Operator for crossover: The number of chromosomes in a population after a crossing with probability B_v *is* d*crosspop* $(d+1)$*.*

5. Operator for mutation: The probability that B_n*can trigger mutations in chromosomally positioned genes. After mutation, the initial population of* d*becomes* d*mutpop*$(d+1)$*. After a round of genetic engineering, the new population is denoted by the equation*$pop\ (d) = mutpop(d+1)$*. It is the progenitor for the following genetic step, which resets the generational counter to 2.*

2.5. Supervised K-Nearest Neighbors (SKNN)

The SKNN method is a popular non-parametric machine learning technique used in supervised learning of new data. Possible uses include those in the fields of regression and classification. The SKNN technique is used for various tasks, such as document analysis, image analysis and handwriting recognition. SKNN would find the node whose coordinates were closest to the testing data class if there was a classification error. A basic set of equations can calculate the distance between the test data and the closest training class. The (i) Euclidean index, (ii) Manhattan index, (iii) Mankowski index, (iv) Hamming index are examples of distance indexes. A formula for calculating distances in Euclidean space.

$$\sqrt{\sum_{j=1}^{r}\left(y_j - x_j\right)^2} \qquad (4)$$

Calculating from Manhattan,

$$\sum_{j=1}^{r}\left|y_j - x_j\right| \qquad (5)$$

Difference of Mankowski,

$$\left(\sum_{j=1}^{r}\left(\left|y_j - x_j\right|\right)^{o}\right)^{1/o} \qquad (6)$$

To compute the Hamming distance,

$$T_Z = \sum_{j=1}^{r}\left|y_j - x_j\right| \qquad (7)$$

A higher value of R produces reliable classification results and reduces noise. $R$is a 3–10-digit number. Algorithm 2 depicts the stages for SKNN.

Algorithm 2: Supervised K-Nearest Neighbors (SKNN)

Stage 1: Input the data set, making the dataset a series of numbers.
Stage 2: Make the feature value normalizedy:
For every feature
$Normalizedvalue = (y - min)/range$
End For
Stage 3: Distance computation in a query Provide the instance's index and distance to finish each case.
Stage 4: Peaking a value of$R$*, getting the labels for that* R*-value.*
Stage 5: If regression fails, revert to the mean of the R *labels. When classifying things, try using the* R *-label average again.*
Stage 6: concludes the categorization with an improved rate of prediction.

3. Results and Discussion

We propose an MGO-SKNN method that outperforms when compared to other conventional approaches like Opposition-Based Modified Mobilenet Pretrained Model (MMPM) (Hammadet et al., 2023), Attention based Convolutional Neural Network (ACNN) (Hammadet et al., 2023) and Convolutional Neural Network (CNN) (Hammadet et al., 2023). In comparison to standard methods, in terms of f1-score, recall, accuracy, and precision, this one performs better.

3.1. Accuracy

A standard definition of accuracy in discussions of flame monitoring or flame detection systems is the degree to which they document and confirm the presence or absence of flames in a specific setting. To calculate the accuracy as a percentage, use the following formula. Figure 5 displays the exact precision of the graphical measurements. The advised procedure has a 94.53% success rate. MGO-SKNN accuracy of 97.53% compared to other popular methods is superior to MMPM's 94.76%, ACNN's 84.70% and CNN's 67%in Table 2. Compared to current methods, the one proposed here is a huge step forward.

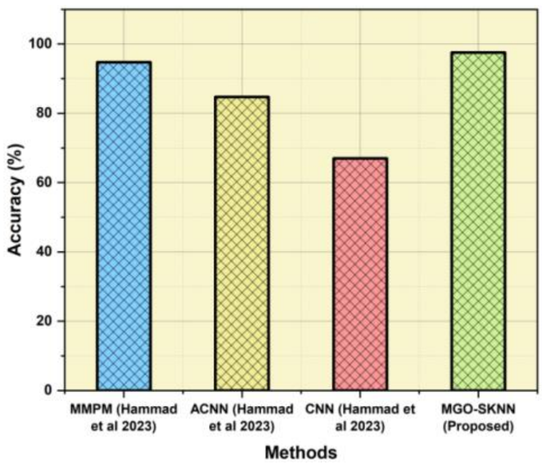

Figure 5 Comparison of accuracy for proposed and existing methods.

Table 2 Numerical outcomes of Accuracy.

Methods	Accuracy (%)
MMPM (Hammad et al., 2023)	94.76
ACNN (Hammad et al., 2023)	84.7
CNN (Hammad et al., 2023)	67
MGO-SKNN (Proposed)	97.53

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (8)$$

3.2. Precision

One approach to measure accuracy is to look at how useful predictive data was uncovered. Treatment and diagnostic accuracy are essential for precise healthcare monitoring. It is crucial in healthcare monitoring since it influences the trustworthiness of the data. The precision of each measurement in Figure 6 is the same.When compared to MMPM (90.6%), ACNN (84.92%) and CNN (90.1%), MGO-SKNN (95.2%) has the best results. The precision numerical results are shown in Table 3. The proposed technique is precise than the standard approaches.

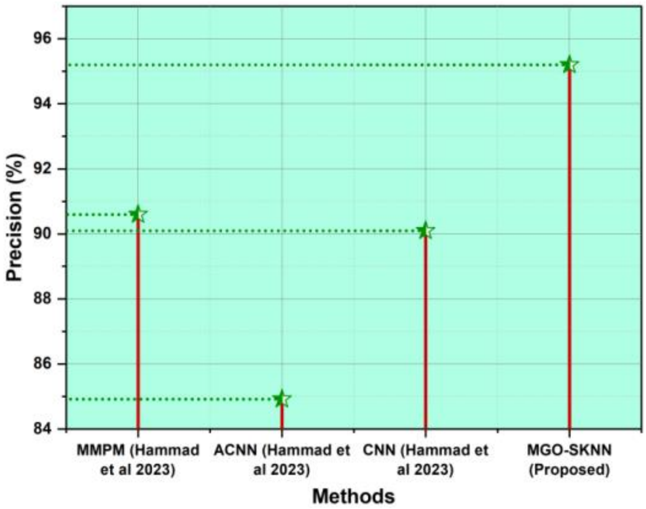

Figure 6 Comparison of precision for proposed and existing methods.

Table 3 Numerical outcomes of Precision.

Methods	Precision (%)
MMPM (Hammad et al., 2023)	90.6
ACNN (Hammad et al., 2023)	84.92
CNN (Hammad et al., 2023)	90.1
MGO-SKNN (Proposed)	95.2

$$Precision = \frac{TP}{TP+FP} \quad (9)$$

3.3. Recall

The recall of a flame monitoring system is the rate at which it identifies and locates actual fires. The system's capacity to detect and prevent data loss due to natural fires is evaluated. Figure 7 demonstrates the graphical recall rates. The recommended method's MGO-SKNN value of 96.74% exceeds MMPM's 93.37%, ACNN's 84.70%, and CNN’s 90.38%. Table 4 provides numerical recall results.

Table 4 Numerical outcomes of Recall.

Dataset	Recall (%)			
	MMPM (Hammad et al., 2023)	ACNN (Hammad et al., 2023)	CNN (Hammad et al., 2023)	MGO-SKNN (Proposed)
1	85	75	87	91
2	92	89	83	95
3	83	73	89	92
4	85	75	88	90
5	81	73	85	96.75

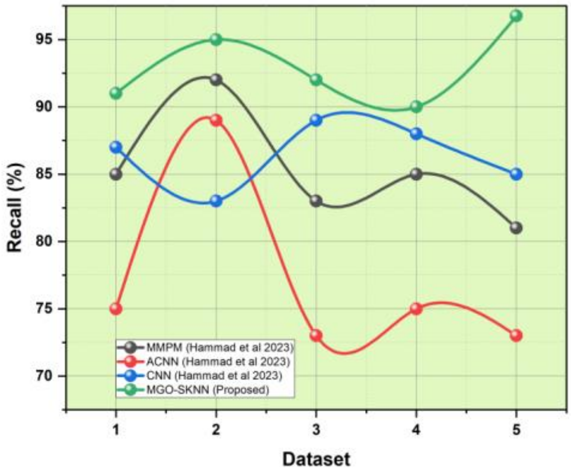

Figure 7 Comparison of recall for proposed and existing methods.

$$Recall = \frac{TP}{TP+FN} \qquad (10)$$

3.4. F1-Score

Statisticians use the F1-Score to measure a binary classification model's reliability and accuracy. The alias is because it is neither totally correct nor easily forgotten. A model's accuracy is quantified by the percentage of instances for which a forecast was correct. The graphical results are shown in figure 8. MMPM for the proposed technique is 91.31%, ACNNis 84.66%, and CNN is 80.38%. Table 5 displays the numerical results for F1-Score. Compared to current approaches, the suggested method MGO-SKNN is more precise (98.06%).

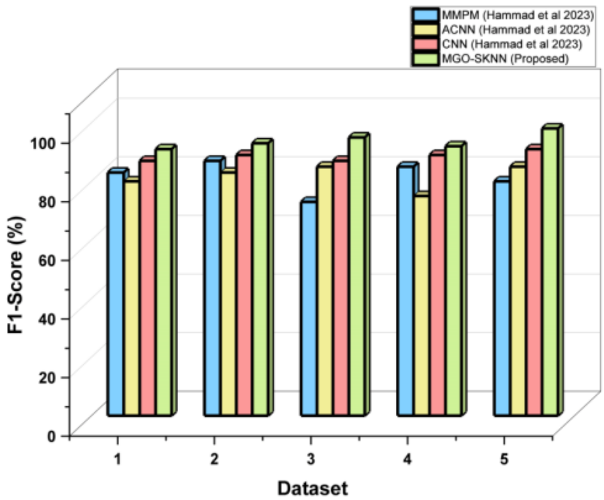

Figure 8 Comparison of F1-score for proposed and existing method.

Table 5 Numerical outcomes of F1-Score.

Dataset	F1-Score (%)			
	MMPM (Hammad et al., 2023)	ACNN (Hammad et al., 2023)	CNN (Hammad et al., 2023)	MGO-SKNN (Proposed)
1	83	80	87	91
2	87	83	89	93
3	73	85	87	95
4	85	75	89	92
5	80	85	91	98.06

$$F1\ score = \frac{2 * (precision * recall)}{(precision + recall)} \qquad (12)$$

3.5. Problem Statement

Expert systems can function in limited contexts. The domain has to be well-defined and easily understood.As the number of diseases increases linearly, the number of possible diagnoses skyrockets. To characterize such a rise in the total number of solutions, the phrase combinatorial explosion is sometimes employed. The topic of skin condition diagnosis is a good match for developing expert systems. The skin is the topic of study for this WES. Some of the skin diseases that our technology can identify are described in detail.

4. Discussion

High-level texture and context interpretation skin identification tasks can be beyond the capabilities of MMPM because of their lack of high-level feature representation (Sae-Lim et al., 2019). ACNN is limited in its applicability because of over fitting on tiny skin datasets and the need of annotated data for training. Lack of clarity hinders comprehension during dermatological examinations (Hasan et al., 2023). Complex skin identification tasks are difficult for CNNs because they cannot detect long-range correlations in skin pictures. Data preparation and inconsistent datasets are barriers to progress in skin identification (Nagaraj et al., 2023). MGO-SKNN uses hyper parameters such as distance metric, neighbors' and feature selection to improve model performance. With minimal human input, the system learns from fresh skin detection datasets, improving accuracy and robustness. Genetic algorithms can improve MGO-SKNN for clinical and non-clinical skin identification.

5. Conclusion

In conclusion, there is a new horizon for the development of precise approaches for detecting skin issues due to the integration of image processing, increased genetic optimization and supervised K-NN. Skin cancer can result from extremes. Skin disease diagnosis from clinical pictures is a key medical image processing challenge. Manual skin diagnosis is subjective and time-consuming for doctors. Computerized skin disease prognoses can facilitate dermatologist-patient therapy planning. These issues were addressed by developing the MGO-SKNN skin disease identification method. This ground-breaking study can benefit public health by altering how skin disorders are identified and treated. New diagnostic procedures for skin illnesses can become more accurate, efficient and accessible as medical technology advances. The system's functionality must be maintained throughout modifications. The system must connect with EHRs, healthcare databases and clinical data for optimal patient care. To address these challenges, hyper parameters like distance metric, neighbors' and feature selection boost MGO-SKNN model performance. With little human input, the system learns from new skin detection datasets to improve accuracy and resilience. Genetic algorithms can enhance clinical and non-clinical MGO-SKNN skin identification. We presented MGO-SKNN for enhanced skin disease detection. Our proposed method, MGO-SKNN, outperforms conventional methods for skin identification on a variety of measures, including accuracy (97.53%), precision (95.20%), recall (96.74%) and f1-score (98.06%).

5.1. Future Scope

Machine learning has the potential to detect treatable skin issues at an early stage. This helps in the detection and prevention of disease. The development of AI that can detect skin disorders has made it possible to keep tabs on one's health through smartphone or telemedicine. If more skin advice were readily available, doctors' offices would see fewer patients. Ready Care's AI-generated treatment plan can consider a user's DNA, lifestyle and skin condition. Error prevention in the healthcare system might lead to greater efficiency and effectiveness. It's possible that adopting a lightweight, basic, AI-powered skin assessment device might help to avoid skin disorders.

Ethical considerations

Not applicable.

Conflict of Interest

The authors declare no conflicts of interest.

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