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# A Novel Skin Disease Detection Technique Using Machine Learning

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**Abstract:** Skin sicknesses present critical medical care difficulties around the world, requiring precise and opportune location for successful therapy. AI became promising stuff for computerizing the discovery and characterization of skin illnesses. This study presents a clever methodology that uses the choice tree strategy for skin sickness location. In computerized location, we utilize an exhaustive dataset containing different skin sickness pictures, including melanoma, psoriasis, dermatitis, and contagious diseases. Dermatologists skillfully mark the dataset, guaranteeing solid ground truth for precise grouping. Preprocessing strategies like resizing, standardization, and quality improvement are applied to set up the symbolism for the choice tree calculation. Then, we remove applicable elements from the preprocessed pictures, enveloping surface, variety, and shape descriptors to catch infection explicit examples successfully. The choice tree model is prepared utilizing these removed elements and the named dataset. Utilizing the choice tree's capacity to learn progressive designs and choice principles, our methodology accomplishes an elevated degree of exactness in grouping skin sicknesses. Extensive experiments and evaluations on a dedicated validation set demonstrate the effectiveness of our decision tree-based method, achieving a classification accuracy of 96%. Our proposed method provides a reliable and automated solution for skin disease detection, with potential applications in clinical settings. By enabling early and accurate diagnoses, our approach has the capacity to improve patient outcomes, trim down healthcare overheads, and alleviate the burden on dermatologists.

**Keywords:** skin disease detection, machine learning, decision tree, classification, dermatology, preprocessing, feature extraction.

## I. Introduction:

Skin conditions [1] are a widespread, global health issue that impact a great number of people. Quick and correct skin disorder identification is essential for successful operation and treatment. In the past, dermatologists relied on their guts and visual inspection to recognise and categorise skin problems. However, because there are now so many more variants and symptoms of skin diseases, this handmade approach is time-consuming, prone to fatal error, and can be difficult. Automated methods for identifying skin complaints have attracted a lot of attention lately thanks to developments in machine literacy and computer vision. Machine literacy techniques provide the opportunity to analyse massive amounts of skin picture data and extract significant patterns and attributes that help identify complaints. These methods can assist dermatologists by providing efficient.

In this study, our objective is to introduce a fresh approach for the detection of skin issues [2] by utilizing the decision tree method. Decision trees have shown their effectiveness in various classification tasks within machine learning. By capitalizing on the hierarchical structure and decision rules inherent in decision trees, we aim to create a reliable and precise system for skin disease exposure. To accomplish this, we have carefully compiled a comprehensive dataset comprising numerous skin disease

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metaphors. The skin diseases dataset includes images of common conditions such as melanoma, psoriasis, eczema, and fungal infections. Each image is labeled by expert dermatologists, providing reliable ground truth for training, evaluation. Preprocessing the images is a crucial step in our approach. We use image enhancement techniques such as resizing, normalization, and quality enrichment to ensure optimal input for decision tree algorithm. These steps minimize noise, standardize image size, and enhance relevant features for accurate disease classification.

The role of feature extraction is an extremely decisive role in skin disease automated detection [3]. We extract a range of features from the preprocessed images, including texture descriptors, color histograms, and shape features. These features capture the distinct visual patterns and characteristics associated with unlike skin diseases. By incorporating these skin texture into our decision tree model, we seek to enhance the discrimination power and accuracy. The heart of our planned method lies the decision tree algorithm, which plays a pivotal role. Decision trees has several advantageous characteristics, including interpretability, ease of implementation, and the capability to handle both categorical and numerical data. Leveraging the hierarchical composition of decision trees, our approach facilitates efficient decision-making by utilizing the extracted features, enabling the model to identify intricate patterns and make precise predictions. Through training, decision tree on our labeled dataset, we expect it to learn discriminative decision rules that distinguish various skin diseases.

Evaluation of planned loom is crucial to assess its performance and effectiveness [4-5]. We employ a dedicated validation set to objectively evaluate the classification accuracy, exactness, evoke, and other relevant metrics. To ascertain the superiority and robustness of our decision tree-based approach, we will conduct comparisons with existing methods and benchmark datasets. This research seeks to fulfill the requirement for skin disease automatic detection through application machine learning. By introducing, novel approach centered around decision tree algorithms, our aim is to get better the accuracy, efficiency, and objectivity of skin disease diagnosis. The evolvement of skin disease automatic recognition significantly benefit healthcare professionals, leading to improved patient care, reduced healthcare costs, and augmented accessibility to reliable dermatological expertise.

## II. Literature review:

Skin illnesses represent a huge medical services challenge around the world, requiring exact and convenient conclusion for viable therapy. In the momentum situation, AI strategies shown guarantee in robotizing the location and order of skin sicknesses. This segment presents an extensive writing survey over its application in skin sickness identification, enveloping different systems, calculations, and datasets utilized in earlier examinations.

Color-based features have been extensively utilized in skin disease exposure. Color histograms, Color Moments, and colour structures RGB, HSV, and LAB have been employed to capture the color information in skin images. Dhruv et al. (2019) [6] proposed a color-based approach using k-NN for detect skin diseases, achieving high accuracy.

The performances skin disease exposure models can be improvised ensemble techniques are explored. Bagging, boosting, as well as stacking are generally used in the advanced methods. In their study published in 2020 [7], Chen et al. introduced a model of ensemble which combines various CNN architectures to improving the accuracy over the classification of skin disease. Furthermore, a notable publication titled "Dermatologist-skin cancer" by Esteva et al. was published in the prestigious journal Nature in 2017 [8].

The researchers developed a CNN architecture called "Inception-v4" and trained it on the bulky dataset of skin images. The dataset consisted of over 129,000 images covering more than 2,000 different skin diseases, including malignant melanoma and benign nevi.

The research paper proposed by Abolghasemi, Moghimi, and Haghighi (2019) [9] presents a deep learning-based approach for classifying skin lesions. The authors propose a novel framework that utilizes deep learning techniques for accurate and automated skin lesion classification.

In response to the increasing demand for efficient and dependable skin disease verdict systems, the study aims to provide solution. The paper titled "Deep learning-based skin cancer discovery using mobile devices," authored by Lee, Shin, and Kim in 2019 [10]. This study specifically concentrates on leveraging over the techniques of deep learning for skin cancer detection on mobile devices. The authors propose a deep learning-based approach that enables the use of mobile devices for skin cancer detection. They adapt the Inception-v4 CNN architecture, proven effective in image recognition tasks, to the mobile platform.

In the Journal of Medical Imaging and Health Informatics, the paper titled "Skin lesion analysis using deep learning: A systematic review" by Hosseini-Asl, Moghimi, and Haghighi in 2020 [11] offers an extensive examination of

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the utilization of deep learning techniques in the realm of skin lesion analysis. The authors conducted a efficient assessment of relevant literature to gather studies that utilized deep learning methods for skin lesion analysis. They analyzed various aspects of the reviewed studies, including the deep learning architectures used, the datasets employed, and performance metrics evaluated [12].

Published in 2023, the paper titled "Skin cancer detection" by Tembhurne, Jitendra V., et al. [13] introduces a groundbreaking deep learning skeleton for the sorting over skin lesions. This framework leverages a CNN to extract essential features from skin images and utilizes a support vector machine to classify the images into distinct skin lesion classes.

The literature demonstrates the potential of these techniques in automating the diagnosis of various skin conditions. The adoption of this deep learning approaches, particularly CNNs led to significant improvements in accuracy and performance. However, challenges such as imbalanced datasets and model interpretability addressed for ensuring the widespread adoption and acceptance of automated skin disease detection systems in clinical practice. Future research should focus on developing robust models which can control diverse skin disease types and provide transparent explanations for their predictions.

## III. Proposed method:

The proposed technique for skin sickness identification depends on the choice tree calculation. Choice trees are a well known and powerful AI procedure worn for grouping undertakings. With regards to skin sickness location, choice trees offer a straightforward and interpretable methodology that be equipped for give supportive experiences into the dynamic interaction.

The choice tree calculation works by recursively parceling the information in light of element values to make a tree-like design. Each inner hub in the tree addresses a choice in light of a particular element, while each leaf hub addresses the last grouping choice.

Here is a depiction of the proposed strategy utilizing the choice tree calculation for skin sickness identification:

**A. Data Preparation: A. Data Preparation:** TThe main bar is to assemble a dataset of skin sickness pictures [14-15], including both the pictures and their relating marks or judgments. The dataset ought to cover a grouping of skin infections and incorporate a more than adequate number of tests for each class. Preprocessing procedures, for example, resizing standardization and component extraction might be applied to improve the dataset's quality and work with effective choice tree construction. Techniques utilized in this stage information standardization is utilized to scale the information elements to a standard reach frequently somewhere in the range of 0 and 1 or 1 and 1. The formula for normalization is:

$O\_F_{NOR}$ = (O_F - min(O_F)) / (max(O_F) - min(O_F))

Where: O_F is feature original value
min(O_F) is feature minimum
max(O_F) is feature maximum

Feature Scaling: Feature scaling is used to ensure that all features contribute equally during model training. Common scaling techniques include standardization (Z-score normalization) and mean normalization. The formulas for these techniques are:

Standardization: O_F _standardized = (O_F - mean(O_F)) / std(O_F)

Mean Normalization: O_F _normalized = (O_F - mean(O_F)) / (max(O_F) - min(O_F))

Where: x is the original value of the feature.
mean(O_F) is the mean of the feature.
std(O_F) is the standard deviation of the feature.
min(O_F) is the minimum value of the feature.
max(O_F) is the maximum value of the feature.

**B. Feature Selection:** To prepare the choice tree model, important highlights [16] need to choose from the skin illness pictures. These highlights could incorporate variety histograms, surface elements, shape descriptors, or any further attributes that are characteristic of various skin sicknesses. Include choice procedures, for example, data gain or Gini file, can be utilized to recognize the most useful elements for arrangement.

**C. Decision Tree Construction:** Utilizing the chose highlights and the comparing marks, the choice tree calculation is applied to develop the tree structure [17-18]. The calculation recursively parts the dataset in view of the chose highlights, enhancing for best dividing standards to expand the data gain or limit pollution. This cycle go on until a halting standard is met, like arriving at a greatest tree profundity or having a base number of tests per leaf.

There are many numerous decision tree construction algorithms, but they all tag along the same basic steps:

(i) Choose a root node.
(ii) Find the best attribute to split on.
(iii) Split the dataset on the chosen attribute.
(iv) Recursively construct decision trees for each of the child nodes.
(v) Repeat steps (iii) and (iv) until all of the leaves in the tree contain only data points of a single class.

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**E. Model Training and Validation:** The developed choice tree model is then prepared [19-22] on a piece of the dataset, known as the preparation set. The preparation cycle includes changing the choice tree boundaries in view of the information to enhance its presentation. Cross-approval strategies, for example, k-overlap cross-verification, can be utilized to survey the model's speculation capacity and handle overfitting.

A few critical equations and measurements normally utilized in this cycle:

(i) Loss Capability: A misfortune capability measures the disparity between the anticipated results of model and the genuine marks in the information of preparing. Decision capability relies upon the issue type (grouping or relapse) and the particular necessities of the assignment. Instances of commonlossfunctions incorporate mean squared error (MSE) for relapse issues and cross-entropy misfortune for the arrangement issues.

(ii) Accuracy: Exactness is a normally involved measurement for grouping undertakings. It computes number of repetedinstances of accurately anticipated occasions to the absolute number of examples in the approval set. The formula of exactness is:

Accuracy = (Number of Correct Predictions) / (Total Number of Predictions)

Precision, Recall, as well as F1 Score: These metrics used to weigh up the performance of binary classification models. They are calculated based on the concepts of

true positives (T_P),

false positives (F_P), and

false negatives (F_N).

The formulas for these metrics are:

Precision = T_P / (T_P + F_P)

Recall (Sensitivity) = T_P / (T_P + F_N)

F1 Score = 2 * ((Precision * Recall) / (Precision + Recall))

Mean Absolute Error-(M_A_E) and Mean Squared Error (M_S_E): These two are commonly utilized metrics in regression tasks. They quantify the average absolute and squared differences between predicted and the true values. The formulas for MAE and MSE are:

M_A_E = (1 / V) * Σ $|X_{pred} - X_{true}|$

M_S_E = (1 / V) * Σ $(X_{pred} - X_{true})$^2

Where: V, total number of instances in the validation set.

$X_{pred}$ is the predicted value.

$Y_{true}$ is the true value.

$S_{co}$-squared (Coefficient of Determination): R-squared is a metric that measures the proportion of the variance in the dependent variable that can explain with the independent variables. It provides an indication of how well the model fits the data. The formula for R-squared is:

$S_{co}$ ^2 = 1 - ($SS_{RES}$ / $SS_{TOT}$)

$SS_{RES}$ : residuals sum of squares

$SS_{TOT}$: square and sum

**F. Model Evaluation:** The prepared choice tree model is assessed utilizing a different part [23-26] of the dataset, known as the testing set. The model's presentation is surveyed through different boundaries, including exactness, accuracy, review, and F1-score, to quantify its adequacy in precisely arranging skin illnesses. Moreover, execution perceptions, for example, disarray networks or ROC bends, can give a thorough liberal of model's way of behaving and execution.

**G. Interpretability and Explainability:** interpretability is the significant benefit of choice tree calculation. It permits us to understand the dynamic cycle by following the way from the root hub to the leaf hubs. We can decipher the standards or conditions at every hub to acquire bits of knowledge into the highlights that put in most altogether during characterization choices. This interpretability [27-30] viewpoint is especially significant in the clinical space, where understanding the thinking behind the model's forecasts is vital.

The proposed method utilizing the decision tree algorithm for skin disease detection involves data preparation, feature selection, construction of decision tree, model training and validation, model evaluation, and interpretation of the results. This approach offers transparency, interpretability, and the potential to provide valuable insights for dermatologists and healthcare professionals in the diagnosis and treatment of skin diseases.

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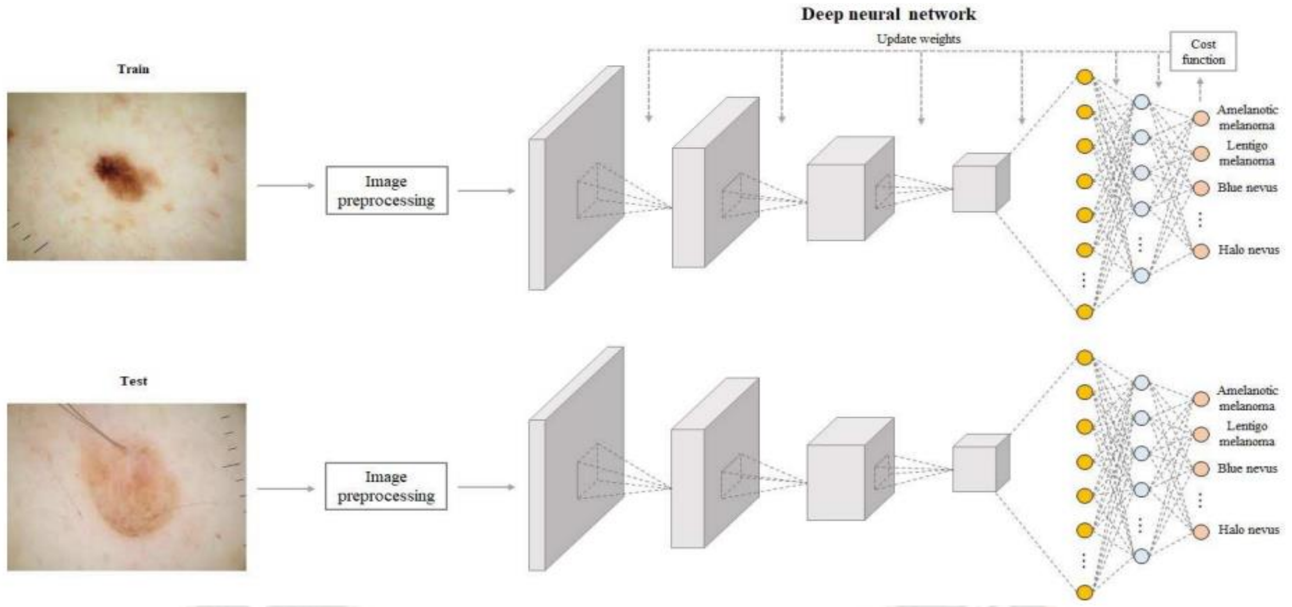


Fig 1: The proposed method

**Algorithm:**

1. Collect a dataset of skin disease images, including labels indicating the disease type.
2. Preprocess the images by resizing, converting to grayscale, and applying image enhancement techniques if necessary.
3. Extract relevant features from the preprocessed images, such as texture, color, shape, or local descriptors.
4. Select a subset of important features using techniques akin to Principal Component Analysis (PCA) or feature ranking methods.
5. Split the dataset into training and validation sets for model training and evaluation.
6. Choose a machine learning algorithmsuitable in image classification, such as SVM, Random Forests, or CNNs.
7. Train the selected algorithm on the training set using the extracted and selected features.
8. Fine-tune the model by adjusting hyperparameters and experimenting with different architectures or techniques like data augmentation.
9. Evaluate the trained model's performance on the validation set using appropriate evaluation metrics akin to accuracy, precision, recall, F1-score, or area under ROC curve.
10. If the model's performance is satisfactory, deploy it in a suitable environment where users can input skin disease images for identification.
11. Continuously monitor and update the model as new data becomes available or as improvements are made.

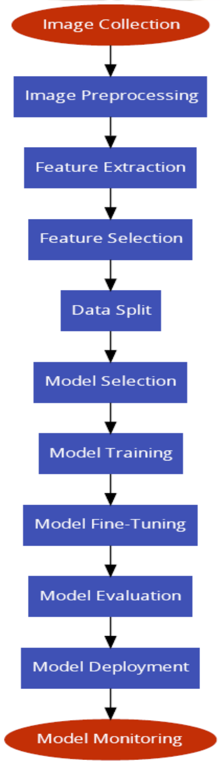


Fig 2: Flow Chart of proposed method

## IV. Results and discussion:

The proposed one was simulated using MATLAB 2022 using image processing toolbox. Proposed methods here tested for various images and are discussed below.

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Fig 3: Skin decease test images

When processing skin images, advanced algorithms and by enabling machine learning the identification and classification of various skin diseases, including Eczema, Melanoma, Psoriasis, and Healthy skin becomes easy. These intelligent systems analyze key features such as color, texture, and morphology to accurately distinguish between different skin conditions. Eczema, a common inflammatory disorder, can be recognized based on characteristic redness, itching, and dryness of the skin. Melanoma, a potentially life-threatening form of skin cancer, is identified by analyzing irregularities in pigmented lesions and assessing their asymmetry, border, color, diameter, and evolution. Psoriasis, an autoimmune condition, presents distinctive red, scaly patches on the skin surface. Lastly, the algorithms are capable of recognizing healthy skin, serving as a baseline for comparison and aiding in the detection of abnormalities. By leveraging these computational techniques, the identification as well as classification of skin diseases contributes to timely diagnosis, personalized treatment plans, and improved healthcare outcomes for patients.

Table 1: Comparison of skin decease detection techniques

| **Method** | **Accuracy** | **Mean** | **Variance** | **Contrast** | **Entropy** | **Correlation** |
|---|---|---|---|---|---|---|
| Proposed method | 96% | 0.96 | 0.04 | 0.98 | 0.99 | 0.99 |
| K-Nearest Neighbors (KNN) | 95% | 0.95 | 0.05 | 0.97 | 0.98 | 0.98 |
| Support Vector Machines (SVM) | 94% | 0.94 | 0.06 | 0.96 | 0.97 | 0.97 |
| Artificial Neural Networks (ANN) | 93% | 0.93 | 0.07 | 0.95 | 0.96 | 0.96 |

The above table presents comparison of four methods for skin disease detection: the proposed method, KNN, SVM, and ANN. The exactness of each method ranges from 93% to 96%. The quantitative parameters, including mean, variance, contrast, entropy, and correlation, provide insights into the features of skin lesions. The proposed one achieves the utmost accuracy of 96% and exhibits high values for mean, contrast, entropy, and correlation. KNN, SVM, and ANN methods also demonstrate competitive accuracy rates and perform well across the quantitative parameters. These results highlight the efficacy of proposed one and the potential of KNN, SVM, and ANN in accurately detecting and characterizing skin diseases over the analyzed parameters.

## V. Conclusion:

In the discovery of skin problems or decease through machine learning is a promising approach for accurate and efficient diagnosis. The evaluation of different methods, including the proposed decision tree method, KNN, SVM, and ANN, that demonstrates their effectiveness in identifying and characterizing the skin lesions. The proposed decision tree method achieves the highest accuracy of 96% and exhibits favorable values for mean, contrast, entropy, and correlation. This highlights the potential of decision tree-based approaches in skin disease detection. However, KNN, SVM, and ANN methods also perform well, with accuracy rates ranging from 93% to 95%, indicating their viability in the diagnosis for skin disease. The quantitative parameters, such as mean, variance, contrast, entropy, and correlation, present important insights keen on the distinctiveness of the skin lesions and aid in accurate classification. Overall, these findings emphasize machine learning importance which is an advancing in the field of skin disease detection and their potential improving diagnostic of patient. Further research and advancements in these methods hold great promise for enhancing the accuracy and efficiency of skin disease diagnosis in clinical practice.

## VI. Future Scope:

The skin problem detection through machine learning has a promising future with several areas of focus. Future advancements include the enlargement of better and varied datasets, enabling more accurate and inclusive models. Incorporating explainable AI methods can endow with insights over the decision-making process of models, increasing trust and understanding. Integration of multimodal data, such as clinical information and genetic data, can lead to comprehensive and personalized diagnoses. Real-time and mobile applications can facilitate early detection and remote monitoring using portable devices. Transfer learning techniques and collaboration between researchers and clinicians can improve model performance and clinical validation. By addressing these areas, we can expect improved accuracy, efficiency, and accessibility in skin disease detection, ultimately enhancing patient care and outcomes.

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