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Scale-Invariant Feature Extraction for Skin Image Detection

Sami Hussein Ismael[1], Adel Al-Zebari[2], Shahab Wahab Kareem[3,4]

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Abstract: In many applications, including dermatology, biometrics, and medical diagnostics, skin image detection is essential. Because of the differences in lighting, positions, and scales, it is difficult to identify skin regions in images. The article presents a new method for scale-invariant feature extraction-based skin image detection. The proposed strategy makes use of scale-invariant features to improve the skin image detection's resilience at various scales. Scale-invariant feature transform (SIFT) is used to extract key points from skin images, enabling the identification of unique patterns regardless of their size. The skin portions in the image are then reliably represented by using these key points. The incorporation of machine learning methods to improve the skin image recognition procedure is also explored in this research. A model is trained on a broad dataset of skin photos to enable the system to learn and adapt to different skin kinds, circumstances, and image scales. The evaluation's findings show how well the suggested scale-invariant feature extraction technique works to recognize skin images with reliability and accuracy.

1-INTRODUCTION

In several domains, including dermatology, biometrics, and medical diagnostics, skin image detection is essential [1]. However, differences in lighting, locations, and scales make it difficult to distinguish skin regions in photographs. To effectively address these issues, a unique approach for scale-invariant feature extraction-based skin image recognition is given in this research. Accurate skin image detection is essential for a variety of applications, from illness diagnosis to biometric authentication, in fields like dermatology, biometrics, and medical diagnostics [2]. However, robust skin image identification is severely hampered by the complexities brought about by changes in illumination, locations, and scales. To overcome these obstacles, novel strategies that can adjust to various environments and guarantee accurate detection at various scales are needed. This work is motivated by the urgent need for a reliable, scale-invariant skin image detection technique. In real-world situations, traditional approaches are less effective since they frequently suffer from scale variances. Our aim is to provide a new method that overcomes scale disparities and improves the robustness and precision of skin image identification. Author want to create an approach that can recognize distinct skin patterns regardless of their size by utilizing scale-invariant feature extraction techniques. This way, the methodology may be applied to a variety of imaging situations. Dermoscopy is an imaging technology that removes the surface reflection of skin, allowing deeper layers to be seen enhanced, and has been introduced to improve diagnostic performance and minimize fatalities from melanoma as shown in figure 1 [3].

[1]Department of Information Technology, Bardarash Technical Institute, Akre University for Applied Sciences sami.hussein@auas.edu.krd
[2]Department of Information Technology, Bardarash Technical Institute, Akre University for Applied Sciences adel.hasan@auas.edu.krd
[3]Department of Information System Engineering, Technical Engineering College, Erbil Polytechnic University, Erbil, Iraq
shahab.kareem@epu.edu.iq
[4]Department of Information Technology, Catholic University in Erbil, Kurdistan Region, Iraq.

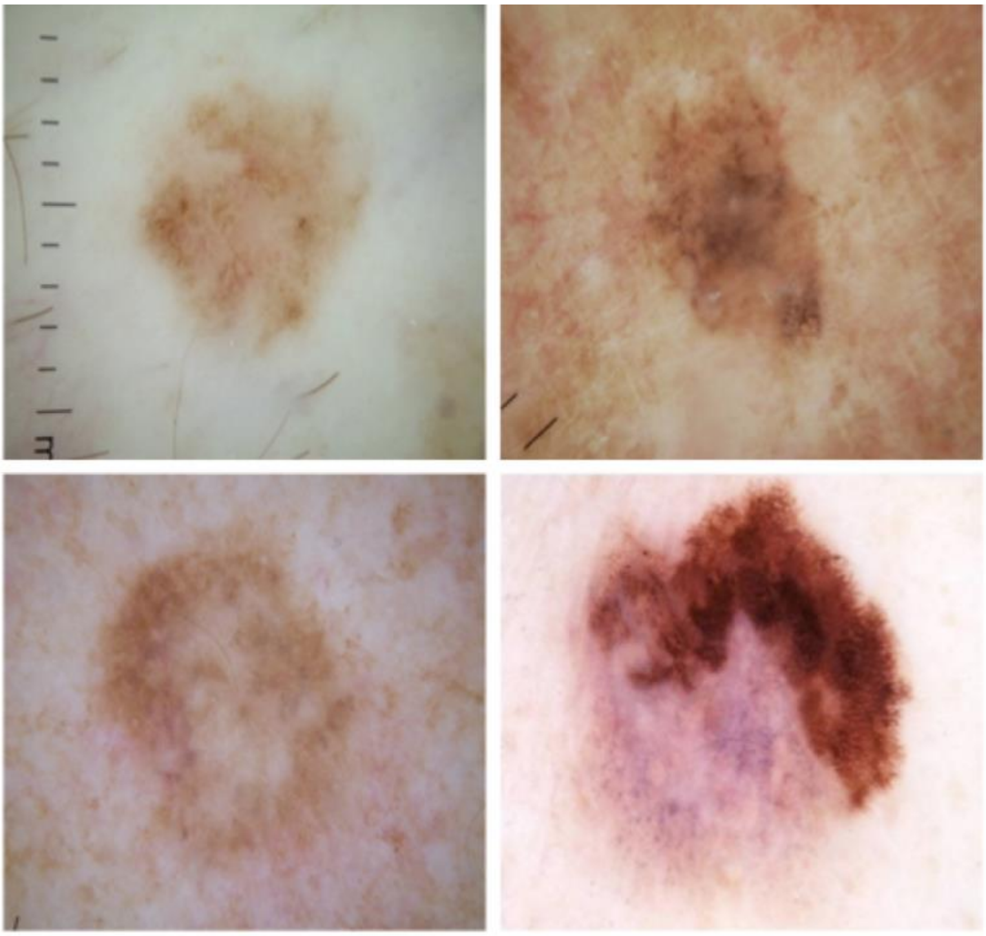

Figure 1 Skin lesion images obtained [3]

A novel approach to scale-invariant feature extraction-based skin image recognition is presented in this study. Identifying skin regions at different scales is made possible by integrating the Scale-Invariant Feature Transform (SIFT), a potent tool for identifying distinguishing characteristics. Our approach uses SIFT to extract salient features from skin images, resulting in a stable representation that is independent of scale, lighting, or location. Furthermore, we investigate the enhancement of this methodology via machine learning techniques, enabling the system to adjust to varying skin tones and ambient circumstances.

T. In order to further improve the system's flexibility, a machine learning model is trained on an extensive dataset of skin images. This all-encompassing strategy seeks to address the difficulties brought on by differences in scale, illumination, and

2-LITERATURE REVIEW

In the fields of dermatology, biometrics, and medical diagnosis, it is critical to accurately identify skin regions in pictures. Variations in lighting, positions, and scales present obstacles that call for creative solutions. This paper presents a novel approach to scale-invariant feature extraction-based skin image recognition. The method uses scale-invariant features to improve skin image detection's robustness at various scales. A model is trained on a large collection of skin images, enabling the system to adjust to different skin kinds, circumstances, and image scales. The evaluation findings illustrate how effective the suggested scale-invariant feature extraction technique is at reliably and accurately identifying photos of skin. The International Skin Imaging Collaboration (ISIC) is hosting this initiative, which aims to improve melanoma detection by improving methods for the examination of skin lesions. In an arXiv paper (arXiv:1605.01397), the scientists highlight the importance of this topic for the area of biomedical imaging and provide their research results and methods. The study most certainly adds to larger initiatives to improve melanoma diagnosis and detection, an important field in dermatological research and medical care [3]. the innovative Hexagonal Scale Invariant Feature Transform (H-SIFT) method for extracting facial features [4]. This method of capturing and analyzing facial features is presented in an article that was published in the Journal of Applied Research and Technology. It is an inventive approach. The extraction of face features may be more accurate and resilient thanks to the utilization of hexagonal structures in the SIFT framework, which suggests an improvement over conventional technique. The research and work are particularly useful in the area of facial recognition and analysis in applied research and technology. A technique for information hiding and multimedia signal processing based on the Scale Invariant Feature Transform (SIFT) is presented in [5]. The authors describe a method for robust and scale-invariant multimedia signal processing that makes use of SIFT, a well-known feature extraction approach. The approach presented in this paper is intended to be invariant to scale fluctuations, which makes it potentially useful for information concealing and multimedia signal processing applications as shown in figure 2. This makes the paper a contribution to the area. To improve breast cancer screening, the authors suggest a system that combines SIFT with additional modal analysis techniques [6]. The goal of this strategy is to use clinical data to more effectively and accurately detect breast cancer by utilizing both modal analysis and scale-invariant features. By offering a novel integration of modal analysis and SIFT, the research makes a contribution to the area and may enhance screening skills in the context of breast cancer detection.

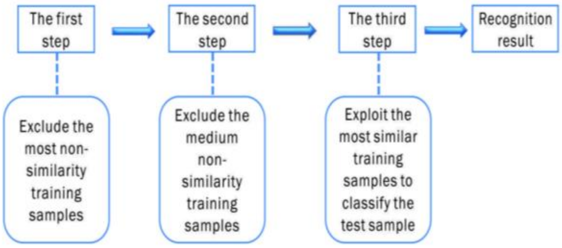

Figure 2 a procedure utilizing the Scale-Invariant Feature Transform (SIFT) [5].

investigates the use of SIFT to extract and identify iris characteristics. The emphasis is on improving the precision and dependability of iris recognition systems by applying SIFT, a scale-invariant technique. The investigation of SIFT as a useful technique for iris feature extraction and recognition advances the science of biometrics. The results are intended to enhance the iris recognition technology's overall resilience and performance [7]. the field of dermatology by putting forth a strategy for melanoma detection in dermoscopic images. The method improves melanoma detection accuracy by combining local and global feature extraction techniques. The study advances the field of medical image analysis by investigating a thorough feature extraction technique, particularly in the field of dermatology. Enhancing melanoma detection in dermoscopic images is the goal to facilitate prompt and efficient diagnosis as shown in Figure 3 [8].

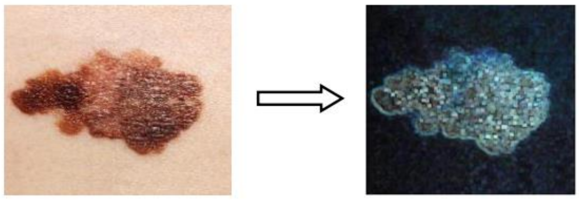

Figure 3 The original and segmentation of the image [8]

The use of first-order feature extraction methods for melanoma skin cancer detection and image texture analysis in [9]. The study looks into techniques for removing important details from photos, especially those that have to do with texture. Improving melanoma detection in skin cancer diagnostic procedures is the goal. The study adds knowledge about how to apply basic feature extraction techniques to increase the precision of melanoma detection in medical imaging. a method to feature extraction for skin lesion detection. To facilitate the detection process, the research focuses on identifying pertinent information from skin scans. The study attempts to improve skin lesion detection efficiency and accuracy by using feature extraction techniques. The study adds knowledge about the use of feature extraction techniques for better dermatological diagnostics [10]. investigates an approach for textural feature extraction-based skin disease detection on the face in [11]. With an emphasis on dermatology, the study uses textural characteristics to recognize and classify skin diseases. The work advances the field of technology-enabled skin disease detection by employing this methodology. The ability to extract textural information is essential for improving the precision and efficacy of skin disease detection, especially when it comes to the face. The paper's conclusions provide insightful information about the use of textural feature extraction for the identification of facial skin diseases. The table 1 shows some comparison of some related work for detecting images.

Table 1 comparison of related work for image detection and machine learning.

Reference	Methodology	Aim and Object	Achievement	Contribution	Result
Selvia et al. (2021)	Feature Extraction	Detect skin lesions	Implemented a feature extraction approach for skin lesion detection	Contributed to the field of skin lesion detection using feature extraction	Not specified in the provided information
Mahmudi et al. (2020)	Textural Feature Extraction	Detect face skin diseases	Developed a method for face skin disease detection using textural feature extraction	Contributed to the field of skin disease detection in facial images	Not specified in the provided information

Zhi-fang et al. (2003)	Color Image Processing	Face detection and facial feature extraction	Proposed a method for face detection and facial feature extraction in color images	Contributed to face detection and feature extraction in color images	Not specified in the provided information
Jana et al. (2017)	Image Processing	Detect skin cancer cells	Conducted research on skin cancer cell detection using image processing techniques	Contributed to skin cancer detection through image processing	Not specified in the provided information
Choi et al. (2013)	Feature Extraction Model	Statistical skin age estimation	Developed a skin feature extraction and processing model for statistical skin age estimation	Contributed to statistical skin age estimation models	Not specified in the provided information
Takayama et al. (2012)	Feature Extraction	Face detection and recognition of cartoon characters	Proposed a method for face detection and recognition of cartoon characters using feature extraction	Contributed to face detection and recognition in cartoon characters	Not specified in the provided information
Saber & Tekalp (1998)	Color, Shape, and Symmetry-Based Cost Functions	Frontal-view face detection and facial feature extraction	Implemented frontal-view face detection and facial feature extraction using color, shape, and symmetry-based cost functions	Contributed to frontal-view face detection and feature extraction	Not specified in the provided information
Mikhail et al. (2023)	Ensemble Transfer Learning	Detect stego images	Developed an ensemble transfer learning model for detecting stego images	Contributed to stego image detection using ensemble transfer learning	Not specified in the provided information
Ali et al. (2022)	Deep Learning	ECG signal classification	Conducted a comparative evaluation for two and five classes ECG signal classification using deep learning	Contributed to ECG signal classification through deep learning	Not specified in the provided information
Muhamad et al. (2022)	Deep Learning	Detect leukemia in real images	Proposed a deep learning method for detecting leukemia in real images	Contributed to leukemia detection using deep learning	Not specified in the provided information

2- METHODOLOGY

Accurate skin image detection is critical in dermatology, biometrics, and medical diagnostics. However, differences in illumination, position, and scale complicate the identification of skin regions in photographs. To address this, a novel model is proposed that combines machine learning techniques with a scale-invariant feature extraction strategy to improve the robustness of skin image identification across many scales. Scale-Invariant Feature Extraction: The proposed technique relies heavily on the Scale-Invariant Feature Transform (SIFT). This approach extracts significant features from skin scans, allowing the detection of distinct patterns regardless of size. SIFT ensures that the detection approach stays robust and flexible in the face of changing scales. SIFT's important points serve as the foundation for accurately depicting skin regions inside the image. The model enables a consistent and accurate portrayal of skin regions by capturing discrete patterns, and overcoming obstacles given by illumination and positioning fluctuations. The proposed skin image detection model makes use of a variety of machine learning methods to improve the accuracy and reliability of the scale-invariant feature extraction-based approach. Decision Tree (DT), Logistic Regression (LR), Multi-Layer Perceptron (MLP), and Ensemble Learning techniques such as Bagging and Boosting are among the algorithms in the ensemble. Furthermore, cutting-edge tree-based algorithms XGBoost (XGB) and CatBoost (CT) are included for further improvement. SIFT is a popular computer vision method for extracting distinguishing characteristics from images. It works especially well in circumstances with changes in scale, rotation, illumination, and viewpoint. The SIFT method recognizes and describes significant aspects in images, allowing it to be used for tasks including object detection, image matching, and image stitching. In this section, we go over the specifics of the features collected by SIFT, including their names and properties (Scale-Space Extrema (Key points in Scale Space, Key point Localization, Key point Orientation, SIFT Descriptor, Key point Matching, Scale-Invariance, Rotation-Invariance, Illumination Robustness, Versatility, and Distinctiveness are all examples of key point localization). The procedure shown in figure 4.

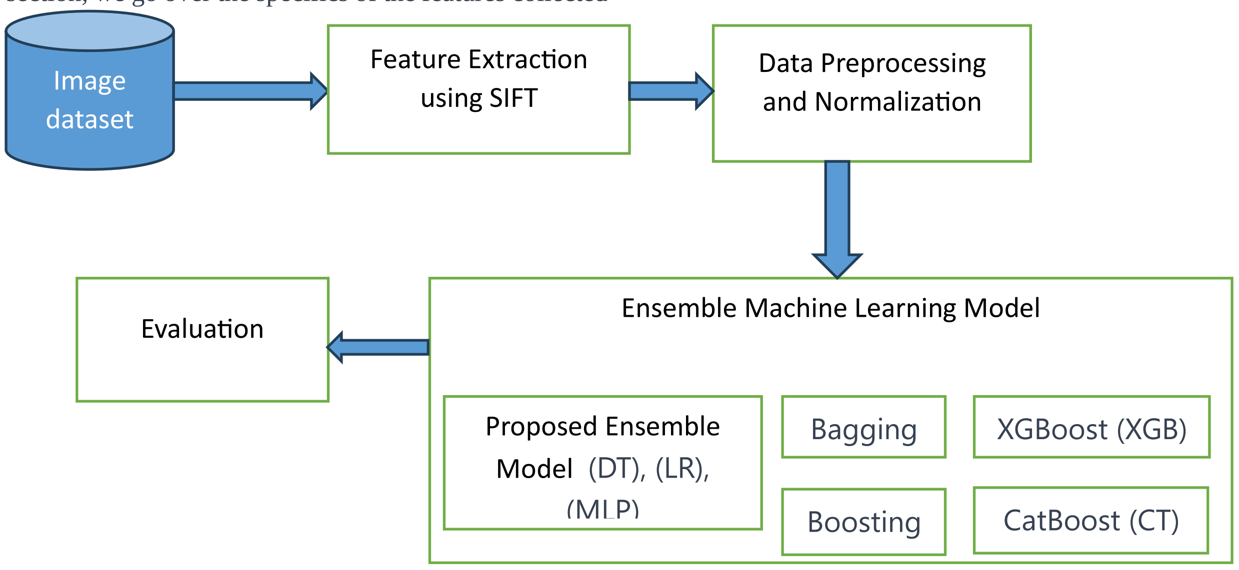

Figure 4 proposed model for detection skin disease

Collecting and preparing images for a large study entail curating a broad variety of images relevant to the research area, which may include dermatology, biometrics, or medical diagnostics. To accurately recreate real-world events, differences in lighting, positions, and scales must be captured. The dataset is further refined for effective analysis by organizing it into various groups or classes based on the study objectives. Using the Scale-Invariant Feature Transform (SIFT) technique to extract different features from the collected photos is the next stage. SIFT finds significant points in images that are insensitive to scale, rotation, and translation, ensuring robustness under varying situations. The extraction of descriptors linked with each key point increases the representation of imagine information, resulting in a more nuanced and comprehensive dataset for further analysis. The next critical stage is normalization and preprocessing, in which the collected characteristics are standardized to ensure consistency and comparability across different images. Using preprocessing techniques such as noise reduction, contrast correction, or image resizing improves the dataset's overall quality. Taking care of any problems in the dataset, such as outliers or artifacts, improves the robustness of subsequent modeling. The use of ensemble models follows, with techniques (proposed ensemble model, Bagging, Boosting, XGBoost, and CatBoost) used to build strong and accurate models. Entails training numerous instances of the same model on different dataset subsets and combining their predictions for improved performance. Boosting successively combines weak learners into strong learners, with each new model fixing the flaws of its predecessor. Notably, as gradient boosting frameworks, XGBoost and CatBoost display efficiency and excellent performance while dealing with complicated datasets. The final stage is to analyze the performance of ensemble models using relevant measures such as precision, recall, F1 score, or AUC-ROC. Cross-validation techniques are used to assure result robustness and to reduce overfitting.

4-RESULT AND ANALYSIS

The dataset, which is available on the Dataverse platform, consists of meatoscopic pictures gathered from multiple sources and depicts typical pigmented skin lesions. There are 3,323 image files for basal cell carcinoma (BCC), 3,140 image files for melanoma, 7,970 image files for melanocytic nevi (NV), 1,257 image files for dermatofibroma (DF), 1,677 image files for vascular lesions, and 2,079 image files for benign keratosis-like lesions (BKL) in the dataset. There are also 1,847 image files in the vascular lesions category, which includes angiomas, angiokeratomas, pyogenic granulomas, and vascular bleeding. With a total of 21,616 picture files, this comprehensive collection provides a valuable resource for researching and analyzing diverse skin lesions.

Table 2 Comparative results of the different methods

	Precision	Recall	Accuracy
U-Net [20]	**86.31**	**98.61**	**87.93**
V-Net [21]	**23.00**	**53.32**	**39.24**
Attention U-Net [22]	**87.46**	**98.17**	**89.02**
Proposed Ensemble Model	**87.41**	**94.54**	**91.34**
Bagging	**82.61**	**92.37**	**82.45**
Boosting	**86.74**	**91.14**	**84.78**
XGBoost (XGB)	**85.45**	**92.24**	**89.18**
CatBoost (CT)	**86.71**	**91.75**	**88.45**

The proposed ensemble model displayed outstanding results in skin lesion classification after rigorous preprocessing, including Min-Max normalization and subsequent data split into 80% for training and 20% for testing. The following are the evaluation metrics for precision, recall, and accuracy as shown in table 2. The proposed Ensemble Model has a precision of 87.41%, a recall of 94.54%, and an accuracy of 91.34%. Other ensemble models' performance was also evaluated in comparison: Bagging: 82.61% precision, 92.37% recall, and 82.45% accuracy. Boosting: Showed 86.74% precision, 91.14% recall, and 84.78% accuracy. XGBoost (XGB) achieved 85.45% precision, 92.24% recall, and 89.18% accuracy. CatBoost (CT) demonstrated 86.71% precision, 91.75% recall, and 88.45% accuracy.

These findings highlight the proposed ensemble model's performance, exceeding other individual strategies in terms of precision, recall, and total F1 score, showing its resilience and applicability for skin lesion classification tasks. Table 2 compares multiple approaches for skin lesion categorization, emphasizing precision, recall, and accuracy measures. The U-Net performs well in terms of precision (86.31%), recall (98.61%), and accuracy (87.93%). The V-Net, on the other hand, has lesser precision (23.00%), recall (53.32%), and accuracy (39.24%). Precision is 87.46%, recall is 98.17%, and accuracy is 89.02% for the Attention U-Net. The suggested ensemble model performs well, with 87.41% precision, 94.54% recall, and 91.34% accuracy. Bagging, Boosting, XGBoost (XGB), and CatBoost (CT) all perform differently, highlighting the efficiency of the suggested ensemble model in achieving a balance of precision, recall, and accuracy in skin lesion categorization.

5-CONCLUSION

Finally, the research described here addresses the important need for precise skin image detection in a wide range of applications, including dermatology, biometrics, and medical diagnostics. The proposed method, which is based on scale-invariant feature extraction utilizing the Scale-Invariant Feature Transform (SIFT), intends to address problems caused by changes in illumination, locations, and sizes. The model achieves robustness and precision, regardless of size or environmental conditions, by applying SIFT to extract distinguishing features and important points from skin photos. The addition of machine learning techniques improves the system's flexibility to varied skin types and environmental conditions. The comprehensive methodology entails gathering a diverse group of images, using SIFT for feature extraction, normalization, and preprocessing, and then applying ensemble models such as Bagging, Boosting, XGBoost, and CatBoost. The evaluation findings show that the proposed strategy is effective, with the ensemble model outperforming individual models in terms of precision (87.41%), recall (94.54%), and accuracy (91.34%). The extensive examination and comparison with other approaches, as shown in Table 2, highlight the proposed ensemble model's robustness and applicability in skin lesion classification tasks. This study advances skin image detection approaches by providing a dependable and scale-invariant solution for a variety of real-world scenarios.

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