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# AI-BASED LOCALIZATION AND CLASSIFICATION OF SKIN DISEASE WITH ERYTHEMA USING IBM WATSON

[1]Kankanala Sri Divya,[2]Dr.M.Swapna(Assistant professor),[3]Ch. Aravind Kumar(Assistant professor), [4]Dr.N.Satyavathi(Associate professor )

*[1,2]CSE, Vaagdevi College of Engineering(Bollikunta, Warangal)*

**Abstract: "**Computer -supported diagnostic (CAD)" have considerably increased diagnostic accuracy in medical areas, including mammography and colonography. Dermatology still depends on non -invasive visual evaluation of doctors, which can lead to findings that are not always the same. To solve this problem, the Ham10000 data file was used to create a complete diagnostic system. This data file has dermatoscopic images with corresponding segmentation maps. "The data file was compiled by making sure that the classification labels were balanced, allowing to divide the data into 50% for training and 50% for testing". We used advanced image processing methods to improve extraction and classification of functions. We used K-Means cluster to divide the image into pieces, and then we used "Support Vector Machine (SVM)" to classify pieces. We also used DL methods such as U-NET architecture with and without deconstruction. U-NET with decomposition method used multi-level image elements to improve the identification and classification of lesion boundaries. Experimental results have shown that U-NET technology worked "much better than other models, with a high sensitivity of 0.9589%". This method works well for the automatic classification and separation of skin lesions, which means less manual control and more reliable diagnosis in dermatology.

***"Index Terms:*** *Artificial Intelligence, Skin Disease Classification, Erythema Detection, IBM Watson, Medical Imaging, Deep Learning, Image Processing, Disease Localization, Dermatology, Computer-Aided Diagnosis".*

## 1. INTRODUCTION

"Computer-aided diagnosis (CAD)" is a sophisticated computer technology that is considerably used in the field of medical imaging that helps medical practitioners to achieve accurate diagnoses. CAD was first used in areas such as mammography and colonography, but now it is a common diagnostic tool in many medical environments, as it can be more accurate and consistent clinical judgments [1] [2]. Although CAD has been shown to be useful in many areas, its use in dermatology was not so widespread. This is particularly worrying because skin disorders are some of the most common health problems in the world and early detection is important for successful treatment and better patient results [3].

Currently, dermatological evaluation of skin disorders depends mainly on visual examination by doctors using uninterrupted eye. Although qualified dermatologists can usually perform accurate judgments, the procedure is subjective and may lead to errors, especially if lesions overlap features or are observed in different lighting [4]. These limitations can cause missed diagnosis or incorrect classification, which would affect the quality of patient care. As a result, the growing need to use the ability of CAD driven AI systems to improve the diagnostic process in dermatology.

Recent breakthroughs in AI, especially deep learning, have offered new ways to identify and classify skin diseases. Segmentation of image and categorization of skin lesions using clustering methods and "support vector machines (SVM) have garnered significant attention [5]. Clustering algorithms such as fuzzy c-means (FCM), improved Fuzzy C-Means and K-Means, created encouraging results". For example, Trabelsi et al. They found that these methods had a true positive segmentation rate of about 83% [6]. Rajab et al. He also looked at the approaches of ISO-DAT cluster to find the best segmentation thresholds [7].

Clustering techniques have several major problems, even if they work well. This is especially true when working with noisy data or photographs with different lighting conditions. These techniques rely on the determination of the centroid to generalize clusters, which makes them susceptible to remote values and noise [5]. To solve these problems scientists including KEKE et al. Developed advanced cluster models using several colors such as RGB, HSV and Lab, thus showing better resistance to such inconsistencies [8].

Dermatology could get a lot of use of intelligent diagnostic tools that integrate the best parts of CAD and AI. This research seeks to illustrate the feasibility of CAD applications in dermatology using advanced deep learning techniques for accurate segmentation and classification of skin disorders.

## 2. LITERATURE REVIEW

Maglogiannis et al. (2006) [9] He designed the advanced segmentation and classification method for pigmented skin lesions using dermatological immatological pictures. They used a combination of extraction and classification methods to recognize the difference between benign and malignant tumors. They used the image to work out and then the statistical methods of recognizing patterns to find important functions. This made it possible to achieve trusted decisions on dermatological assessments.

Albawi et al. (2017) [10] focused on the cultivation of comprehensive grasping of "convolutional neural networks (CNN)", which are widely used in the analysis of the medical image for their ability to learn the spatial hierarchy of information through the convolution. Their research offered extensive clarification of CNN architecture and described in detail the functions of convolution, activation, association and fully interconnected layers that are necessary for deep learning based on diagnostic systems of skin diseases.

"Selvaraju et al. (2019) [11] GRAD-CAM developed (activation mapping of the Dear Gradient Class)", a method designed to offer a visual clarification of deep networks. GRAD-CAM helps find the basic parts of the image that helps the CNN model to express your judgment. This technique improves the interpretability of DL models in medical diagnostics, allowing practices to understand the reasons for the classification of the specific skin condition.

Gutman et al. (2016) [12] have established an "International Symposium on Biomedical Imaging (ISBI) challenge through the International Skin Imaging Collaboration (ISIC)", which helps to find melanoma using dermoscopic images. The competition provided a basic data file and promoted the creation of automated systems for segmentation and classification of lesions. Their study has determined a phase for standardizing how to test AI models for lesion analysis.

Codella et al. (2017) [13] Furthermore, the initiative of ISIC by introducing the second competition at ISBI 2017, which focused on three key tasks: segmentation of lesions, dermoscopic elements and disease classification. Their research has shown the superiority of DL models, especially CNN, above conventional ML techniques, and emphasized the need for complex data sets and clearly joint metrics in dermatological research AI.

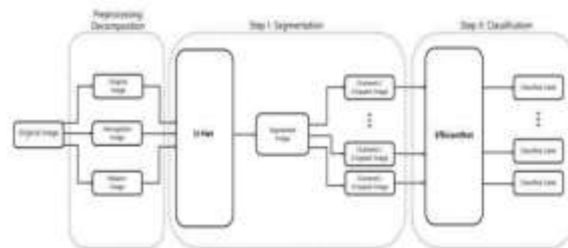
Tschandl et al. (2018) [14] introduced the HAM10000 data file, an extensive compilation of dermatoscopic images with seven types of pigmented skin lesions. This publicly accessible data file has established itself as a standard in AI dermatological research, promotes repeatability and facilitates the creation of generalizable classification algorithms. The Ham10000 has many different types of lesions and imaging conditions, which makes it easier to train deep models that work well in clinical situations in the real world.

Tsumura et al. (1999) [15] They proposed the use of an “independent component analysis (ICA)” to explore the skin colors. Their approach tried to isolate elements of melanin and hemoglobin from the skin tone and therefore increases the visibility of skin lesions. The use of ICA facilitated pathological features in dermoscopic images and helped with more accurate segmentation and analysis characteristics of skin diseases.

Hyvärinen and Oja (2000) [16] have improved ICA by developing efficient computational techniques and presented its usefulness across several domains, including medical imaging. They talked about how ICA could help separate statistically independent sources from mixed signals. This is particularly useful in dermatology where skin textures or lighting changes can hide lesions. Their work provided the theoretical basis to prepare an image using ICA.

## 3. MATERIALS AND METHODS

The proposed system seeks to automate the identification and categorization of skin lesions using modern image processing and DL methodologies. The HAM10000 data file, which has dermatoscopic immatoscopic images with built -in segmentation maps, was used for segmentation and classification tasks. The data file was evenly divided between training and testing, with 50% of the data used for each. To improve the location of lesions, clustering K-significant was first used to segment the image. The “support vector machine (SVM)” was used with DL models for categorization. The system uses U-NET architecture, both with and without deconstruction, for better finding the boundaries of lesions to capture contextual data on different scales. This mixed method improves both segmentation accuracy and classification power [1] [2] [3].



“Fig.1 Proposed Architecture”

The architecture shown shows a three -stage procedure for classification of skin diseases. For better extraction of the elements, the original image is first divided into hemoglobin and melanin maps. In Step 1 U-NET performs very accurate segmentation. In step 2, segmented images are grouped and cut off and then sent to efficiency to be divided into disease labels. This method improves accuracy by a successful combination of decomposition, segmentation and classification. Hybrid framework, such as this, were very good at medical imaging points [1] [2].

**a) Dataset Collection:**

The HAM10000 data file was used to build this system, a huge set of dermatoscopic images of conventional pigmented skin lesions. It has 10 015 high quality images, each with an associated segmentation mask and diagnosis. The data file includes a wide range of lesions such as melanoma, nevus and keratosis, so the classification training is complete. The data file for this system was balanced, with the same 50% division between training and testing sets based on classification labels. This allowed a thorough evaluation of performance and obtain consistent results for segmentation and classification.

**b) Pre-Processing:**

There were many important phases in the preliminary processing phase to ensure that the data file was ready for accurate analysis. First, all photos were created the same size to make the input data consistent. The filtration techniques were used to deprive noise and to improve the brightness of the image. We took the segmentation masks from the HAM10000 data file and sorted them with the right photos. To remove distortion, the data file was divided into two same parts: "50% for training and 50% for testing depending on classification labels".

**Normalization:**

Normalization changes the levels of pixel intensity in dermatoscopic images so that they are all on the same scale, usually between 0 and 1. By becoming the same intensity, neuron networks can better focus on basic skin properties such as texture, colors and lesions. This makes segmentation and classification across different display settings and devices more accurate.

**Resizing:**

The health size ensures that all input images are changed to the same size so that they can be used by the input layer of DL models. This phase is essential for dose processing and maintaining the same resolution of the same, which allows the function of a "convolutional neural network (CNN)" extract. The size change also makes the computer's work more difficult without losing important images, helping to speed up training and make better memory and maintain skin patterns that are important for diagnosis.

**Augmentation "(Rotation, Flipping, Scaling)":**

Increasing the data increases the training data file more diverse by turning, turning it horizontally and vertically inverting it and scaling. These methods imitate how images are taken in the real world, such as from different angles or orientations, and help prevent the model from overcrowding. Enlargement increases the ability of the neural network to generalize to new, unnoticed images, thus increasing the robustness and accuracy of the system in authentic dermatological contexts.

**c) Algorithms:**

1. **"K-means method":** It is used for the first step of the image segmentation that groups pixels depending on how similar colors are. This helps to find areas of lesions before their classification.
2. **"SVM method":** It is used to discover the best hyperplan to classify segmented skin lesions and make sure that different types of lesions are put into the right category.
3. **"U-Net without decomposition":** It is used to divide skin lesions into groups by the structure of the encoder that captures important spatial information.
4. **"U-Net with decomposition":** Improved segmentation by combinations of functions from different levels, which makes it easier to find boundaries and facilitate lesions.

## 4. EXPERIMENTAL RESULTS

**"Sensitivity":** Sensitivity is a way to find out how well the test or tool can find a problem in humans. It comes to see how many people test a positive state compared to how many people actually have it.

$$Specificity = \frac{TP}{(TP + FN)}$$

**"Specificity":** If you want to find out, you take the number of people who have tested the negative state, and divide it with the total number of people who have no condition, which includes both those who tested negative and those who tested positively but did not have this disease.

$$Specificity = \frac{TN}{(TN + FP)}$$

**"Dice Coef":** A cube coefficient is a statistical tool that will help you find out how similar two samples are. People often use it to compare the expected segmentation with the real ground truth in performing tasks of image segmentation. Score 1 on the cube scale means that both things overlap perfectly, while the score 0 means they don't overlap at all. When working with unbalanced data sets, this statistics is quite useful because it treats just like false negatives and false positives.

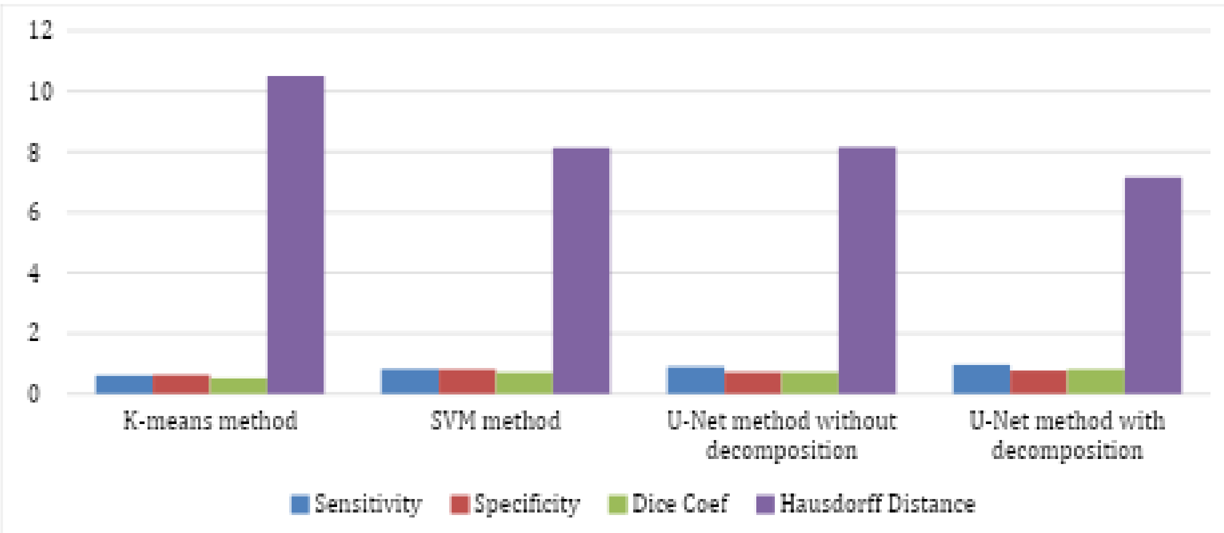
$$Dice\ Coefficient = \frac{2TP}{2TP + FP + FN}$$

***"Table (1)***," The show compares the segmentation "methods using four metrics: green for sensitivity, light green for specificity, light blue for cube coefficient and U-NET method with decomposition. LSTM" gets the best score. Metrics from other methods are also listed for comparison.

"***Table.1*** Performance Evaluation Table"

| Method | Sensitivity | Specificity | Dice Coef | Hausdorff Distance |
|---|---|---|---|---|
| K-means method | 0.6148 | 0.6324 | 0.5165 | 10.487 |
| SVM method | 0.8200 | 0.8100 | 0.7123 | 8.138 |
| U-Net method without decomposition | 0.8953 | 0.7205 | 0.7215 | 8.153 |
| **U-Net method with decomposition** | **0.9589** | **0.7682** | **0.8126** | **7.165** |

"***Graph.1*** Comparison Graph"




***Graph (1)*** "The compares segmentation "methods using four metrics: green for Sensitivity, light green for Specificity, light blue for Dice Coefficient, **U-Net method with decomposition"** and dark red for Hausdorff Distance, which dominates across all methods.

## 5. CONCLUSION

In conclusion, the use of a "Computer-Aided Diagnosis (CAD)" to look at skin lesions significantly improves the accuracy and consistency of dermatological diagnoses. The system was created to quickly handle segmentation and classification tasks using the HAM10000 data set, which has dermatoscopic images and high -resolution segmentation maps. The data file was prepared in advance to make sure it was evenly distributed, with 50% of the data being prepared for training and 50% on the basis of classification labels based on classification labels. The first step in the image segmentation was the use of K-SEPTULATION to find areas of lesions. The second step was to use a "Support Vector Machine (SVM)" to classify lesions. In addition, the U-NET design was used in two configurations: one without decomposition and the other with decomposition. The deconstructed U-NET model used extraction of multi-level elements to better capture the edges of lesions and the fineness of the skin texture. "The U-NET approach worked best from all methods with a sensitivity of 0.9589%. It was better than common U-Net, svm and K-Means methods". This research shows how DL and advanced image processing techniques cooperate on automatic classification of skin diseases. This

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method shows many promises for helping dermatologists, reducing errors in diagnosis and providing a solid, non -invasive way to find and analyze skin problems soon.

In the future, this system can be improved by adding more diverse and larger dermatological immatological immatological images. This would be more useful for people with different skin tones and unique skin disorders. Using Smartphones to analyze images in real time can make it easier for people to get remote diagnostics. To improve accuracy, DL models can be used in future development. Integration of clinical metadata with image inputs could also help dermatologists make better clinical decisions by providing them more complete and context diagnosis.

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