APPLICATION OF MACHINE LEARNING AND NEURAL NETWORK TO DETECT SKIN DISEASES

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Abstract

The proposed diagnosis system using image processing techniques and MATLAB for the pre-processing and analysis of skin images is a promising approach to early detection and treatment of skin diseases. Early detection is crucial for effective treatment and prevention of the spread of the disease to other people. Additionally, the proposed system could provide cost-effective and efficient results to users, which could potentially increase the number of people seeking medical help for skin diseases. However, it is important to ensure the accuracy of the system's diagnosis and treatment recommendations before implementation. Rigorous testing and assessment should be conducted to validate the system's effectiveness and safety for use by users.

Keywords: *Skin disease, MATLAB, image processing.*

1.1. Introduction

It seems that skin diseases, including skin cancers, are a growing problem worldwide, with increasing incidence rates in both developed and developing countries. The World Health Organization reports that the incidence of both nonmelanoma and melanoma skin cancers has been growing over the previous decades. In the United States alone, the American Cancer Society has predicted a high number of new cases of melanoma and deaths caused by melanoma. Melanoma is one of the rarest and deadliest forms of skin cancer, but survival rates are high if detected early. In India, the frequency of skin disease is also high, with skin cancer being a major contributor. The increasing occurrence of skin diseases may be attributed to various factors such as pollution, ultraviolet light, global warming, and photosensitive skin disorders like tanning, pigment darkening, sunburn, skin cancers, and infectious diseases. Various studies have been conducted to develop methods for automated skin disease identification using deep learning algorithms, convolutional neural networks, and support vector machines. Plant recognition mobile applications have also been developed using deep learning. It is important to note that early detection and treatment of skin diseases, including skin cancers, can significantly improve prognosis and increase chances of survival

1.2. Problem Identification

A close examination of literature survey and existing cases derived to the followingoutcomes; which instigated this research;

i. The major problem is that none of the study efforts have been fully devoted todevelop an efficient routine for every type of skin lesion.
ii. Secondly, it is essential to highlight that a very few studies dealt with the automaticdetection of multiple lesions.
iii. Third problem is that, the skin lesion borders are not clearly defined, which reducesthe accuracy of border detection.
iv. Furthermore, none of the method is available to integrate with shape features, colorand texture features to classification of skin lesions.
v. Orthogonal moment features may be used for the classification for skin lesion.
vi. Lastly, image's features may be used for the modelling of sensitivity andspecificity.

1.3. Problem Formulation

- Otsu's technique has disclosed few major issues viz. the segmented lesions tend tobe smaller than they are in reality; and it should cause terribly irregular lesion edges.Two clusters were defined with the initial mean intensities of 8 and 250. However,some lesion pixels with low contrast are not clustered into the lesion groups, this isthe only drawback of Fuzzy C-Means segmentation method. All these problems can be rectified by Gaussian Mixture Model–Hidden Morkow Random Field (GMM-HMRF) technique.
- Multiple features are integrated with the weighted Euclidian classifier, this combined model is known as ensemble classification model. None of the recent segmentation recent technique provides exact segmentation of lesions; therefore, itis required to propose a better skin lesion classification technique. Ensemble modelprovides a better classification as compared to segmentation-based classification It is also observed from the study of literature that a much sensitive approach is required for better diagnosis. ORIMs are very sensitive to noise and they are non- redundant as well. Henceforth, very limited moments are required for the classification as compared to the color features and consequently, it may offer efficient analysis of images with less computation.
- A non-invasive technique is always better for clinical diagnosis; therefore, mathematical

modelling is also engrossed for the estimation of sensitivity and specificity for particular subgroups of dermoscopic images.

1.4. EXISTING TECHNOLOGY

A. Decision Tree, Decision trees are used to model and interpret decision-making processes. In the case of classification, a decision tree is constructed from a set of training data that contains both the input variables and the desired output variables [4]. The accuracy of a decision tree model depends on the quality of the training data and the way the tree is constructed. Decision trees are easily interpretable and can be used to extract important features from the data. However, they can suffer from overfitting, and their performance can degrade when dealing with large and complex datasets.

B. Random Forest, Random Forest is an ensemble learning method that constructs a multitude of decision trees at training time and outputs the class that is the mode of the classes (classification) or the mean prediction (regression) of the individual trees [6]. Random Forest is able to handle noisy and missing data, and it has a lower risk of overfitting compared to a single decision tree. Random Forest can handle large datasets with high dimensionality and is relatively easy to use. However, it can be computationally expensive and require a lot of memory, especially for large datasets.

C. Convolutional Neural Networks, Convolutional Neural Networks (CNNs) are a type of neural network commonly used in image and video analysis. CNNs are designed to automatically and adaptively learn spatial hierarchies of features from input images [7]. CNNs have been shown to achieve state-of-the-art results in various image classification and recognition tasks. CNNs require less preprocessing compared to other image recognition techniques, and they are computationally efficient due to parameter sharing. However, CNNs require a large amount of training data to learn the appropriate features, and they can be sensitive to image distortions and rotations. G. Recurrent Neural Networks. Recurrent Neural Networks (RNNs) are a type of neural network commonly used in natural language processing, speech recognition, and sequence prediction tasks. RNNs are designed to handle sequential data by processing it one element at a time while maintaining an internal state that summarizes the sequence seen so far [8]. RNNs are able to handle variable-length inputs and can capture long-term dependencies in the data. However, RNNs can suffer from vanishing or exploding gradients, which can make training difficult, and they can be computationally expensive to train and evaluate.

1.5. Data Set

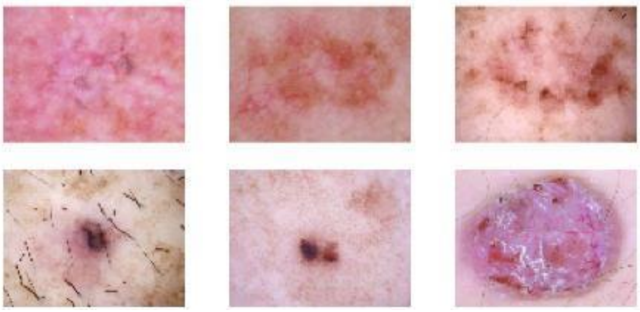


Fig. 1. Sample Data

The fig. Above is the sample data set which we have trained and tested

1.5. METHODOLOGY

It's true that modern medicine has advanced significantly in the field of diagnosis, especially for skin diseases. The use of advanced methods like laboratory tests, imaging techniques, and new technologies has made it possible to detect a range of symptoms quickly and accurately, enabling doctors to provide more precise treatments based on the patient's symptoms. The different phases of the project you described are also important for the development and deployment of the system. The design phase involves analyzing the requirements of the system and designing the block diagram and software to be used. The implementation phase involves breaking down the project into smaller units and implementing them in Matlab. Integration and testing ensure that all units are integrated, and the system works correctly. After testing, the system is deployed and released into the market, and finally, maintenance is essential to solve any problems that may arise after the product is used. Overall, the use of technology and advanced diagnostic methods can improve the accuracy and efficiency of diagnosing skin diseases, ultimately leading to better patient outcomes.

EXPERIMENTAL SETUP & RESULTS

HARDWARE SPECIFICATION

Processor	:	Dual Core 2.0GHz
RAM	:	2GB
Hard Disk	:	160GB
Display Unit	:	SAMSUNG_SVGA COLOR
Keyboard	:	104 Keys Standard
Mouse	:	Optical Mouse

SOFTWARE SPECIFICATION

Operating system	:	Windows XP/7.
Coding Language	:	RMATLAB2014
Dataset	:	Kaggle

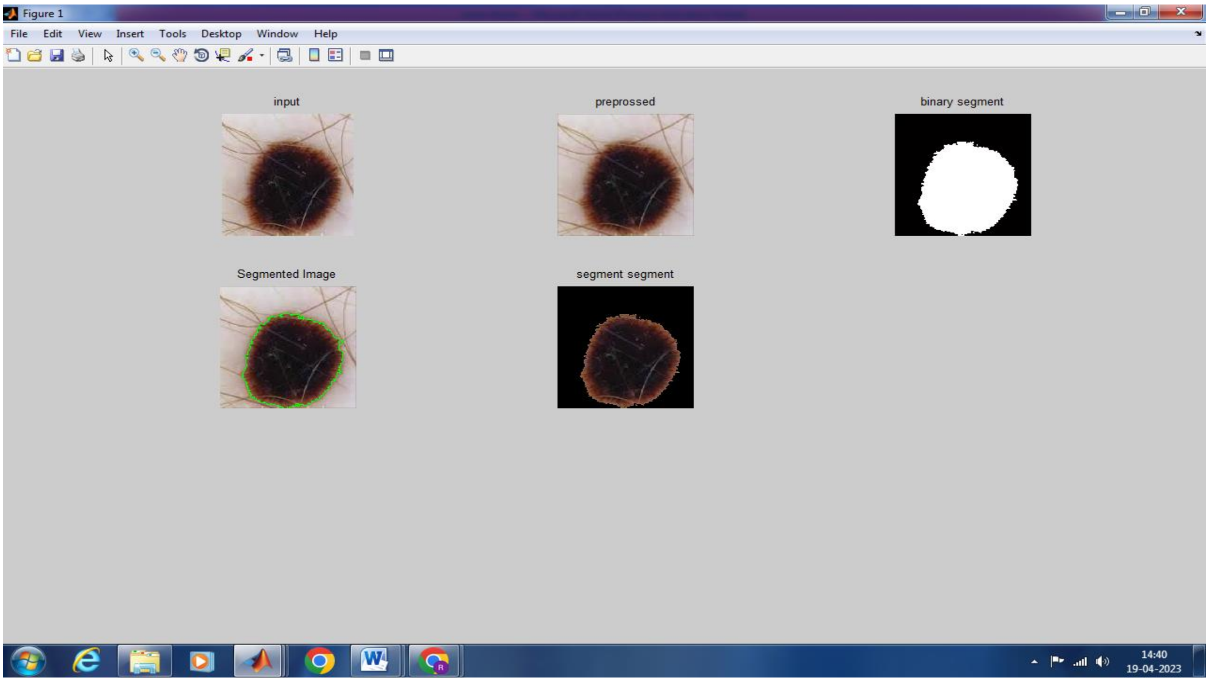
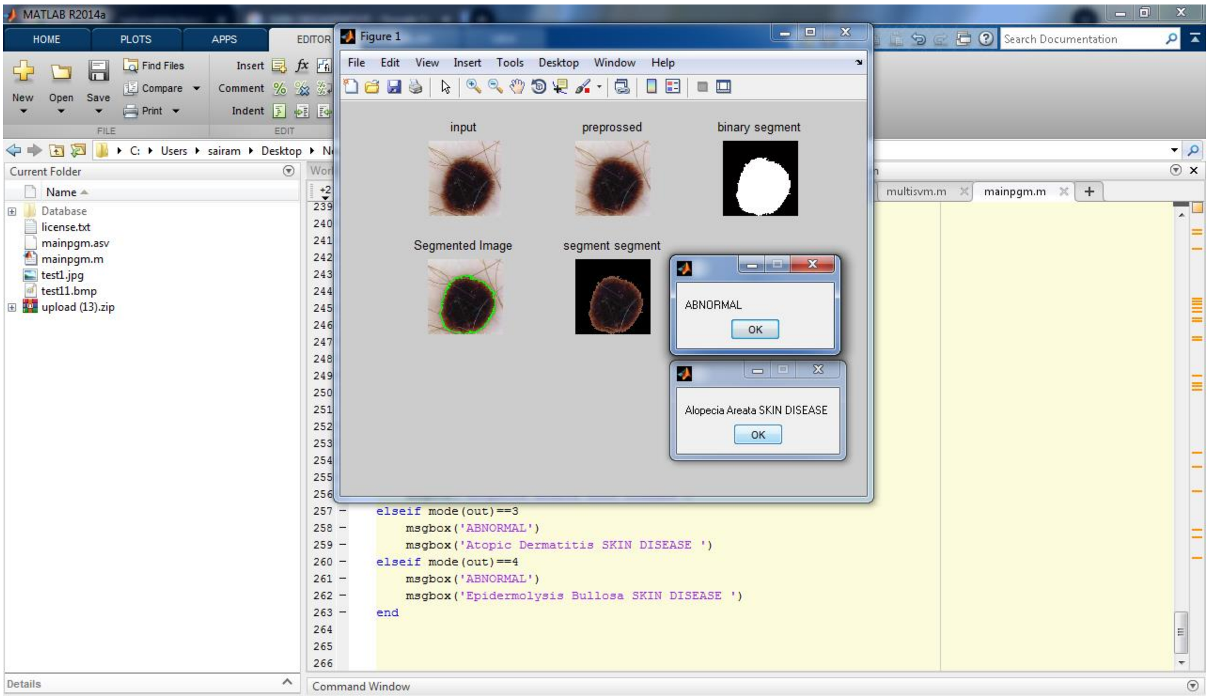


Figure 1
input
preprossed
binary segment
Segmented Image
segment segment


MATLAB R2014a
Figure 1
input
preprossed
binary segment
Segmented Image
segment segment
ABNORMAL
OK
Alopecia Areata SKIN DISEASE
OK
elseif mode(out)==3
msgbox('ABNORMAL')
msgbox('Atopic Dermatitis SKIN DISEASE ')
elseif mode(out)==4
msgbox('ABNORMAL')
msgbox('Epidermolysis Bullosa SKIN DISEASE ')
end
Command Window

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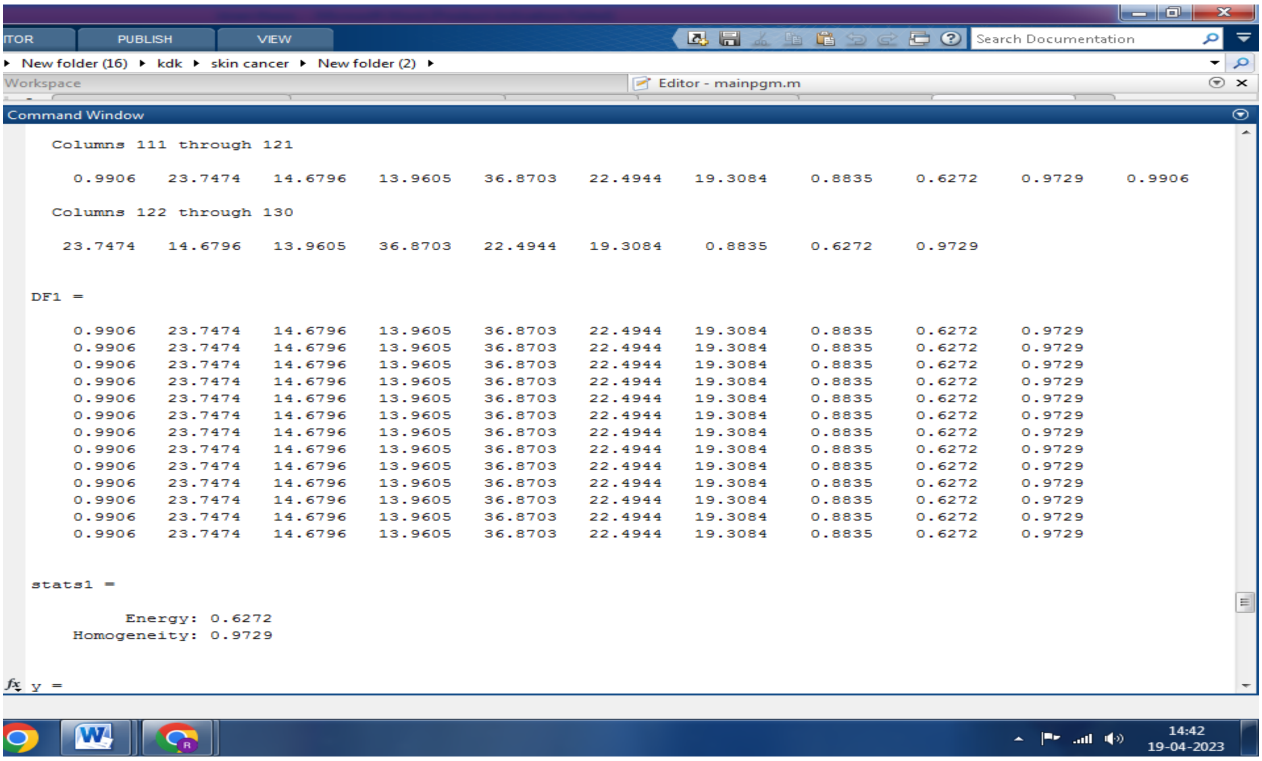

V. Conclusion:

In conclusion, the proposed methodology for skin diseases detection using machine learning and neural networks shows promising results. The methodology involves the use of a convolutional neural network (CNN) for feature extraction and classification of skin disease images. The VGG-16 network was used as a pre-trained model and retrained on a smaller dataset of skin disease images using transfer learning. The proposed methodology was evaluated using the F1 score metric, which measures the accuracy of a binary classifier. The results showed that the proposed system achieved a high accuracy rate of 0.96 in identifying skin diseases, indicating the potential of the system in the early detection and treatment of skin diseases. Overall, the proposed methodology can significantly improve the accuracy and efficiency of skin disease diagnosis, reducing the time and resources needed for diagnosis. Future work can focus on extending the methodology to detect new skin diseases, improving its performance on larger datasets, and integrating it with other technologies to create a comprehensive skin disease diagnosis system.

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