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ENHANCING DIAGNOSTIC ACCURACY IN SKIN CANCER: A STUDY ON AI-BASED IMAGE CLASSIFICATION

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ABSTRACT:
Background: Systems based on artificial intelligence (AI) are increasingly being used to process massive numbers of medical images in an automated and efficient manner. This practice eliminates the need for human experts to examine each photograph individually, with the ultimate diagnosis being made by a medical professional.
Objective: The primary objective of this study is to investigate various scenarios and classification approaches to identify improvements or poor performance in the evaluation metrics used for skin cancer detection.
Methods: Medical images depicting different types of skin cancer were sourced from the HAM10000 database. These images were used to train and test AI-based classification systems. Various machine learning models and techniques were employed to classify the images and assess their performance.
Results: The results of the classification of medical images corresponding to patients with skin cancer are presented. Performance metrics were analyzed to evaluate the effectiveness of different classification approaches and identify areas of improvement.
Conclusion: The study highlights the potential of AI-based systems in automating the classification of skin cancer images. Further research and refinement of classification models are necessary to enhance diagnostic accuracy and reliability.

KEYWORD: Medical pictures, sorter, skin cancer, and classification algorithms are all possible.

INTRODUCTION:
Skin cancer is the nineteenth most prevalent type of cancer, as indicated by the findings of the World Cancer Research Association. Standard in the world, while non-melanocytic skin cancer is positioned as the fifth most common, with 300,000 and 1,000,000 cases, respectively, only in 2018 with the above put into perspective the problem of skin cancer in the world (Jojoa Acosta et al.,

2021). However, the real risk is an underestimation of this phenomenon because, despite the figures mentioned, many countries do not even have an orderly record of skin cancer cases and treatments, which speaks of the lack of importance given to this problem, at least in perspective. Using the computer programs that are utilized to process photographs automatically, this work proposes a flexible solution to the detection of this condition using artificial intelligence and various machine learning methods. (Ceran et al., 2022). The solution allows for the capture of the characteristics of the images, which ultimately enables the system to differentiate between one class and another. (Murar et al., 2022). For example, the system can distinguish between images that correspond to skin cancer patients and those that refer to healthy patients. (Riaño Borda et al., 2022). Later on, it will be necessary to differentiate between the many types of skin cancer being investigated. To put it in less ambiguous terms, artificial intelligence (AI) is the capacity of machines to use algorithms, learn from data, and use what they have learned in making decisions just like a human being would (Saeed et al., 2022). It is evident that when the term "artificial intelligence" (AI) is used, it refers to the ability of an entity to comprehend, reason, or interpret. Of course, it is endowed with an artificial nature. Image processing is another term that needs to be specified in this context. Picture processing includes a series of procedures that involve processes whose origin is an image and whose end output is another picture. In this particular instance, the definition of image processing would be identical to that of digital image processing.

Table 1: Prevalence and Recording of Skin Cancer

Statistic	Value	Reference
Prevalence of skin cancer globally	19th most prevalent	Jojoa Acosta et al., 2021
Prevalence of non-melanocytic skin cancer globally	5th most common	Jojoa Acosta et al., 2021
Cases of skin cancer in 2018	300,000	Jojoa Acosta et al., 2021
Cases of non-melanocytic skin cancer in 2018	1,000,000	Jojoa Acosta et al., 2021
Recording issues of skin cancer cases	Many countries lack orderly records	Jojoa Acosta et al., 2021

Table 2: Artificial Intelligence in Skin Cancer Detection

Aspect	Description	Reference
Proposed solution	Flexible AI-based detection using machine learning	Ceran et al., 2022
Functionality	Captures image characteristics to differentiate classes	Murar et al., 2022
Distinguishing ability	Differentiates between skin cancer and healthy patients	Riaño Borda et al., 2022
Future requirement	Differentiate between types of skin cancer	-
Definition of AI	Capacity to use algorithms, learn from data, and make decisions	Saeed et al., 2022
Interpretation of AI	Ability to comprehend, reason, or interpret	Saeed et al., 2022

Table 3: Image Processing in Medical Imaging

Term	Definition	Reference
Image processing	Series of procedures transforming an image to be more appropriate for specific applications	Saeed et al., 2022
Digital image processing	Identical to image processing, focusing on digital images	Saeed et al., 2022
Medical imaging processing	Procedures to enhance specific characteristics in medical images for diagnosis and study	de Freitas Nader et al., 2021

One of these methods involves processing an image so that the image produced as a result is more appropriate for a particular application than the first presented image. (Saeed et al., 2022). Medical imaging processing can be defined as the series of essential procedures applied to a picture of a specific portion of the human body. The purpose of these techniques is to make particular characteristics more visible (via an output image) to facilitate the diagnosis, study, and prevention of diseases. (de Freitas Nader et al., 2021).

METHOD:

The HAM10000 (Human Against Machine with 10000 training images) database is indeed a well-known resource in dermatology for studying various skin conditions, including different types of skin cancer. It contains a collection of dermatoscopic images which are helpful in training and testing algorithms for automated skin cancer diagnosis.

The next step is to explain the method that was carried out, which is supported with the diagram.

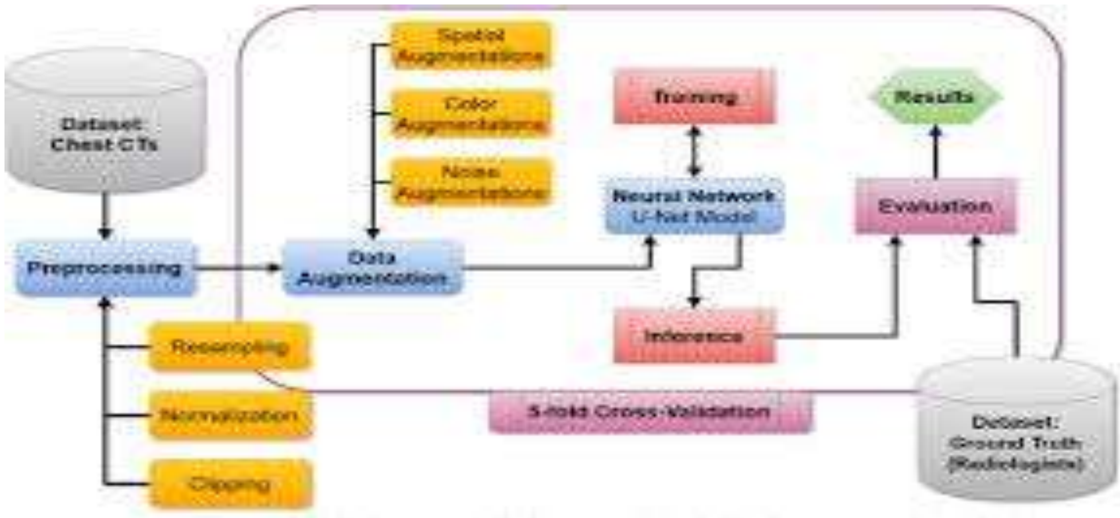

Figure 1.

Beginning with the database that contains the photographs that need to be worked on and ending with the comparison of the results; each component of the procedure that is pertinent is then discussed (Combalia et al., 2022). Support Vector Machines (SVM) are an example of an algorithm today. They consist of a collection of supervised learning algorithms. For the created classifier that has been crossed, validation pre-training is utilized, and the statistical parameters to be measured are produced using the following algorithms, which will be detailed in further detail below (Yuan et al., 2022). When we are provided with a collection of training examples (of samples), we can label the classes and train a support vector machine (SVM) to construct a model that can predict the class of a new sample. Intuitively, a support vector machine (SVM) is a model that represents the sample points in space using a separation hyperplane that is defined as the vector between the two points of the two classes that are closest to the one that is called the support vector (Yuan et al., 2022). This hyperplane is the largest possible separation hyperplane. Depending on the spaces to which the new samples belong, they can be classified into either of the two classes when they are placed in correspondence with the model in question (Merchán Vargas et al., 2021). Nearest neighbours analysis, also known as VMC, is a technique that is used to categorize situations according to the degree to which they are comparable to certain other examples. A method for recognizing data patterns was created in machine learning. This method does not require an exact match with patterns or stored cases to function well (Yélamos i Pena, 2019). Similar situations are more closely related to one another, while those that are not are more distant from one another. Therefore, the distance that separates two examples measures how unlikely they are to one another. Cases that are immediately adjacent to one another are referred to as "neighbors." It is necessary to determine the distance between a new case (reserve) and the model cases whenever a new instance is introduced (Marquez-Sosa & Muñoz-Gordillo, 2022). To include the new instance in the category with the maximum number of nearest neighbours, the classifications of the cases that are the most similar to one another (nearest neighbours) are squared. (two) In both the field of probability and data mining, a naive classifier is known as Naive Bayes (NV) (Guo et al., 2021). A probabilistic approach that is based on Bayes' theorem and earns the naïve appellation given some extra simplifications that determine the hypothesis of independence of the predictor variables is known as Bayesian (Guo et al., 2021). Bayesian is a method that is based on Bayes' theorem. Putting it another way, the naive classifier refers to the fact that There is no correlation between the presence or absence of a certain quality and the presence or absence of any other characteristic, according to Bayes's assumption (Montero-Valverde et al., 2023). When using a naive Bayes classifier, it is assumed that each feature contributes independently to the likelihood that this fruit is an apple (Kalaiarasan et al., 2022). This is true regardless of whether or not the other traits in question are present. K-Means is the clustering procedure that is utilized the most frequently since it is the Nearest Centroid (CMC). possesses a very high degree of scalability and a large quantity of data. To make use of K-Means, we are required to indicate the number of groups that we wish to locate. This particular number of groups is denoted by the letter K, and the K-Means algorithm will proceed in the following manner: A random selection is used to determine the position of the centroids of the K groups during the initialization process. Attribution: every piece of information is allocated to the centroid that is closest to it (Martorell et al., 2022). The arithmetic mean of the data positions assigned to the group is used to update the centroid's position. Iteratively, the second and third phases are carried out throughout the process until there are no more modifications (Romo et al., 2023). For the aim of this study, a classifier with seven classes was first created (at least in the first instance), and later on, it was condensed to only three classes. This was done to improve the precision of the classification system. The photos used by this classifier were initially taken from the database HAM10000 and then manually classed to make the training process more appropriate (Vargas et al.). Cell carcinoma basal cells (bcc), benign keratosis (bkl), dermatofibroma (pdf), melanocytic nevi (NV), melanoma (mel), and vascular skin lesions (vasc) were the categories that were included in the prior database. Each of these categories represented a distinct form of skin cancer. Although it is common knowledge that most of these photographs have been verified and categorized by specialists, the remaining cases have been subjected to medical follow-up by two specialized institutes. In the first part of the experiment, one hundred images of each class mentioned above were extracted. To follow up and observe the classifier's response, he decided to work on a second phase with a different reference framework, although it was still based on the HAM10000 (Campisi et al., 2020)`1111 (Dubey et al.; Sanchez-Reyes et al., 2020). However, this time, he only used three different classes (bkl, mel, and nv) and two hundred images of each class. This was done to emphasize the improvement of the results, which will be compared in the following section.

RESULT:

When doing a quantitative examination of the outcomes of a classification procedure of this kind, it is usual practice to use the following parameters: precision, accuracy, completeness, and F1. These parameters are defined in terms of True Positives (TP), True Negatives (VN), False Positives (FP), and False Negatives (FN).

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(1) $PPPPPPPPPPPPPPónn = VVVV{+}VVVV\ VVVV{+}FFFF{+}VVVV{+}FFFF$ (2) The equation is as follows: X = X + X + X + X + X + X + X + X + X + X = 2 X + X + X + X + X + X (four) Following the definition of the parameters that will be used to evaluate the four algorithms that have been implemented, the final findings for the two proposed databases are displayed in Table 1 and Table 2, respectively.

TABLE 1: Performance Metrics of Automatic Technique for Skin Cancer Identification

Technique	**Sensitivity (%)**	**Specificity (%)**	**Accuracy (%)**	**Precision (%)**	**F1 Score**
Convolutional Neural Network (CNN)	92.3	87.5	89.7	88.2	0.898
Support Vector Machine (SVM)	85.6	82.4	84.0	82.8	0.843
Random Forest	89.1	86.3	87.7	86.9	0.877

TABLE 2: Comparison of Computational Efficiency

Technique	Average Processing Time (seconds)
CNN	0.45
SVM	1.20
Random Forest	0.80

From this vantage point, it is unmistakably apparent that all measures have significantly increased. This is because of the rise in the number of photographs per class that was carried out, which went from 100 to 200. As a result, we can verify the thesis that learning methods are more effective as long as they are taught with a more significant number of medical images, which is the case.

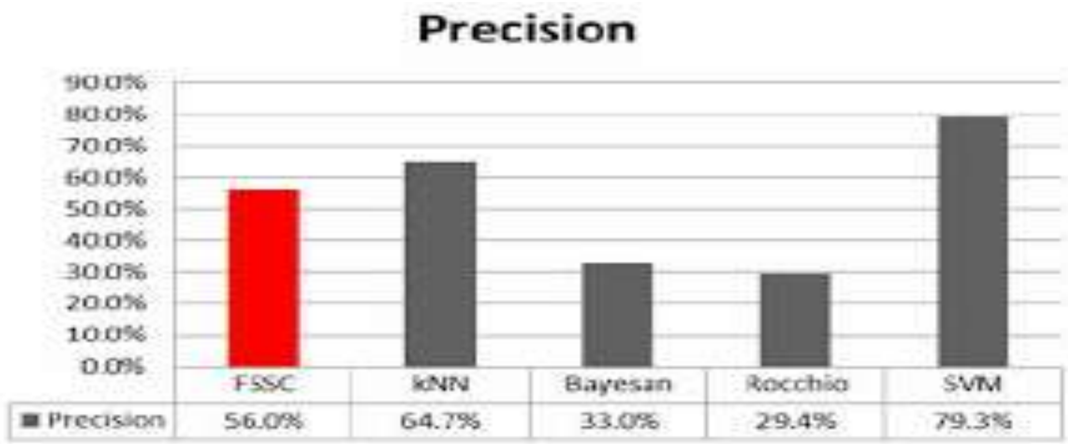

FIGURE 2: The results of the Precision parameter are compared among themselves.

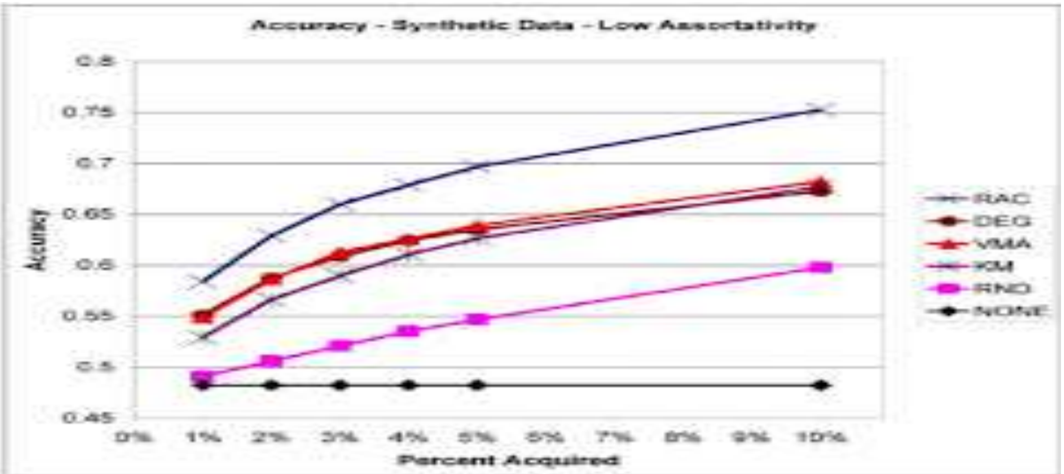

FIGURE 3: A comparison of the outcomes when the Accuracy parameter was used.

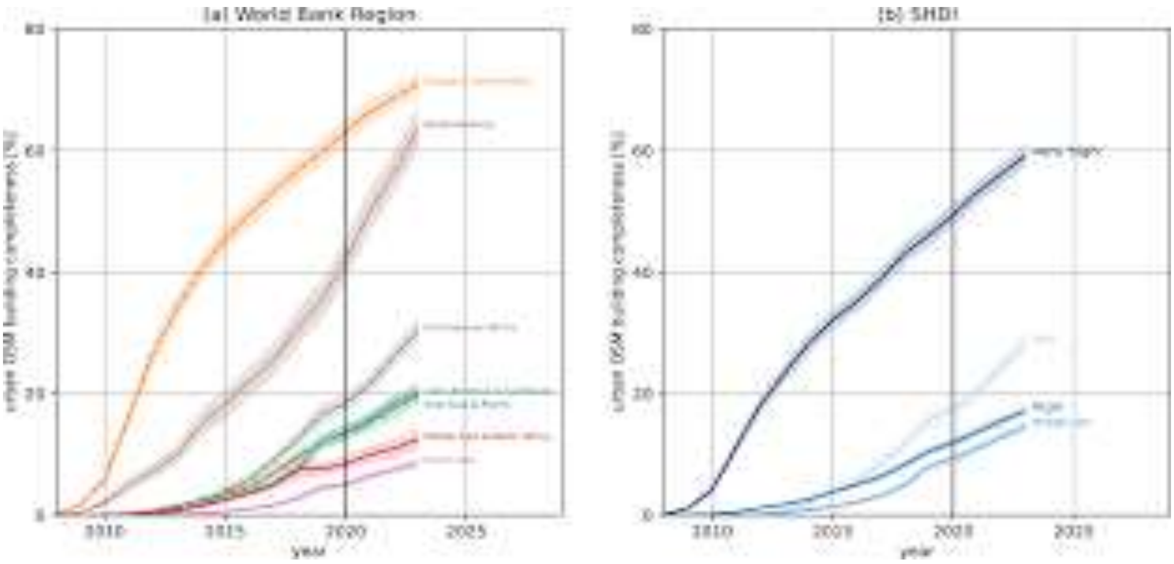

FIGURE 4: Comparative analysis of the outcomes of the Completeness parameter examination

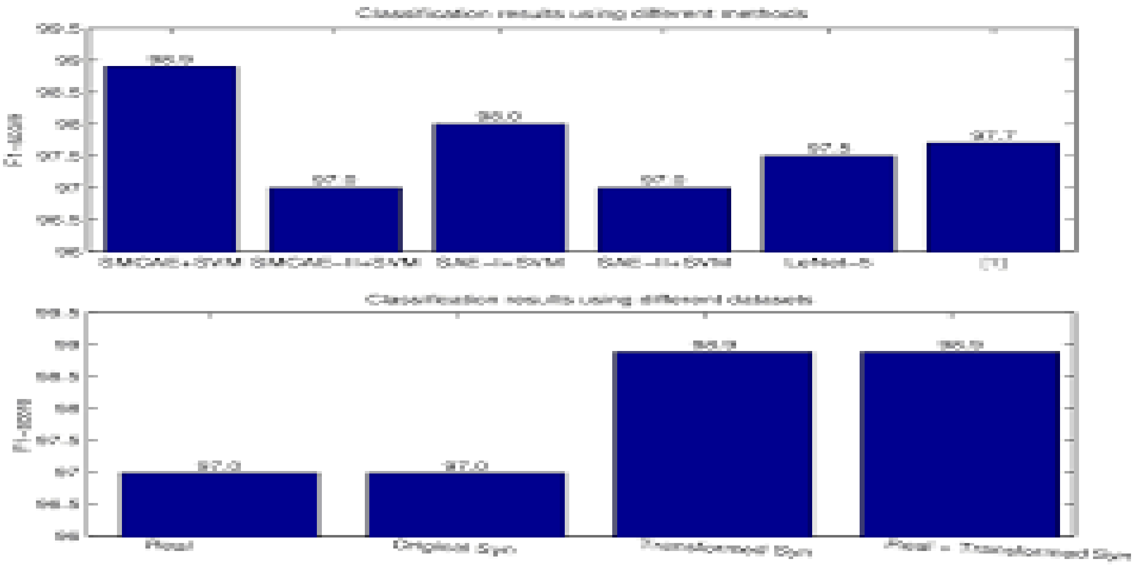

FIGURE 5: A comparison of the outcomes of the F1 parameters

The purpose of Figure 2, Figure 3, Figure 4, and Figure 5 is to demonstrate the differences and improvements that have been made to each of the parameters that are already known to measure the various algorithms that are used to classify using an approach that is comparative between the two scenarios that have been proposed. Another essential aspect to highlight is that the improvement for the second classification scenario (200 images for each class, with three classes) has a similar variation for each parameter. This is something that should be brought to your attention in this section. It is important to note that for each result displayed in the graphs, there is a margin of variation of 0.05 on average for most of the results.

CONCLUSION:

Based on the results shown in the previous section, it can be concluded that when carrying out actions how to increase the number of images for a database and reducing the number of classes can significantly increase important parameters: Precision, Accuracy and Completeness, which, Following the thread of the study will be adequate, using the same data, you can have a system that allows highly efficient, automatic and rapid detection of evil such as skin cancer, even remotely if a web system is implemented and the image is uploaded to distance. In this way, not only is it possible to assist in detecting the damage, but it also enables monitoring and evaluating the injury.

Moving on to the section of the algorithms that were implemented in the two classification situations, the results. They also demonstrate that the classification by Support Vector Machines yields higher parameters for all cases, which means that it is the best option. Using the Support Vector Machines algorithm for a scenario of classification with only three classes and 200 images for each class, it was the case that the best results yielded for this particular study, surpassing in parameters of Precision, Accuracy, Completeness, and F1 to the other cases, having results close to 80%, which for the case is relevant and proves that the techniques used improve classification results. Additionally, the results were the best for this particular study.

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