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Skin Disease Classification Using Machine Learning Algorithms

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Abstract

The most prevalent illnesses in the world are skin diseases. Their tough skin texture, presence of hair on the skin, and colour make diagnosis exceedingly challenging. To improve the diagnostic accuracy of many kinds of skin disorders, techniques like machine learning must be developed. The application of machine learning methods in the medical profession is common for diagnosis. In order to decide, these algorithms employ feature values from photos as input. The feature extraction stage, the training stage, and the testing stage are the three steps of the procedure. Utilizing different skin imaging datasets, the technique trains itself using machine learning technologies. The goal of this procedure is to improve the diagnosis of skin diseases. Texture, colour, form, and their combinations are three crucial elements in picture categorisation. In this study, the skin illness is categorised using criteria of colour and texture. The hue of healthy skin differs from that of diseased skin. Using texture attributes in the photos, it is possible to distinguish between smoothness, coarseness, and regularity. In order to successfully diagnose skin illness, these two traits are investigated. In this study, the Hue-Saturation-Value (HSV) characteristics' entropy, variance, and maximum histogram value are employed. These characteristics are used in the Decision Tree (DT) and Support Vector Machine learning algorithms (SVM). Entropy is employed to divide the tree at the first level. Variance is employed at the second level to get leaves for texturing. In colour features, the HSV measure's highest histogram value is utilised to break the tree. The suggested algorithm's performance is evaluated using accuracy.

Key Words: Image processing, Skin diseases, Machine learning, Feature extraction

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Introduction

The field of healthcare is not an exception to the trend of artificial intelligence (AI), which is quickly becoming the most frequent kind of automation across all sectors. The unexpected appearance of these ailments along with the intrinsic complexity they possess have been a source of growing concern over the last several years due to the elevated danger they provide to human life. As a result of the high degree of contagiousness shown by these anomalies of the skin, urgent treatment is required to stop the spread of the condition. The vast majority of illnesses are brought on by unprotected exposure to the UV radiation that the sun emits (UR). Malignant melanoma is more difficult to treat than benign melanoma, which also puts the patient at a lower risk of complications. In comparison, the most dangerous kind of skin cancer is called malignant melanoma. According to the findings of the study, the back and lower extremities, in addition to the trunk and upper extremities, are more likely to develop skin cancer. Patients often range in age from 30 to 60 years old; this is the most common demographic. In addition, melanocytic nevi, carcinomas, and dermatofibromas are very uncommon in individuals under the age of twenty.

Learning the complex relationships between input and output is the goal of artificial neurone networks (ANNs), a statistical nonlinear predictive modelling technique. The architecture of the ANN was inspired by the organic pattern of a neurone in the human brain.

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Nodes in an ANN are responsible for computation in one of three ways. Artificial neural networks may learn to do computation at each node by using a process called back-propagation. Data sets may be classified as either "trained" or "untrained." The accuracy is produced by a supervised learning technique in the training data sets, and by an unsupervised learning approach in the untrained data sets. Accuracy is achieved in the untrained data sets by the use of a different neural network design, such as a feed forwards approach or a back propagation method, which makes use of the data set in a different manner. The accuracy reached by AI researchers using convolutional neural networks is just 80%, which is far from perfect. Further, ANNs need multi-core, parallel-processing CPUs. Although ANN provides a remedy for probing, it does not provide any clues as to why or how it occurs; this reduces the network's reliability.

The Support Vector Machine (SVM) is a supervised non-linear classifier that generates an ideal n-dimensional hyper-plane to split all of the data points into two categories. [SVM] Selecting a trustworthy kernel function in SVM is not a simple task. It takes a significant amount of time to train on huge datasets. Because the final model is tough to work with, we are unable to do tiny calibrations on it, and it becomes more difficult to tweak the parameters that are used in SVMs. SVMs consistently provide superior outcomes when tested against ANN.

Literature Survey

Diseases of the skin are the fourth most prevalent cause of skin burden in the globe. In order to alleviate some of this strain and to provide patients with assistance in performing an early evaluation of a skin lesion, a dependable and automated method has been devised. The majority of the time, this categorisation method that is offered in the literature is solely for skin cancer. When detected at an earlier stage, treatments for skin are more successful and cause less disfigurement; yet, research into these treatments is difficult owing to the similarities between many skin illnesses. Within the scope of this initiative, we aim to identify skin illnesses. This body of research introduces a brand new method for the diagnosis of the most prevalent skin lesions (Melanocytic nevi, Melanoma, Benign keratosis-like lesions, Basal cell carcinoma, Actinic keratoses, Vascular lesion, Dermatofibroma). The method that has been suggested is based on the pre-processing phase, the Deep learning algorithm, the phase of training the model, the phase of validation, and the phase of classification. Experiments were run on a total of 10010 photos, and the results showed that Convolution Neural Networks

(CNN) combined with the Keras Application Programming Interface obtained an accuracy of 93% for seven-class categorisation.

The ABCD rule-based and computer aided approaches both have the potential to significantly enhance the accuracy of melanoma diagnoses. These systems typically comprise of distinct units, one for picture segmentation, one for feature extraction, and one for classification, in that order. Research carried out in this area includes the following:

Baldrick et al. when classifying the lesions, they compared the results of expert opinion with those of artificial neural networks in their study. They achieved a sensitivity of 95% from the computer programme and a specificity of 88%, while they estimated the sensitivity and specificity of the expert dermatological examination to be 95% and 90% respectively.

Moataz et al. using a genetic algorithm in conjunction with an artificial neural network as a method for early diagnosis of skin cancer, we were able to achieve a sensitivity of 91.67% and a specificity of 91.43% .

Kamasak et al., Following splitting the dermoscopic pictures, the classification of the dermoscopic images were accomplished by extracting the Fourier IDs of the lesion edges. They were able to diagnose the melanoma with an accuracy of 83.33 percent overall.

Fidan et al., Using an artificial neural network that was developed specifically for melanoma and atypical skin malignancies, we were able to achieve a success rate of 93.33% in terms of accurate classification according to the data that was retrieved from the PH2 data set.

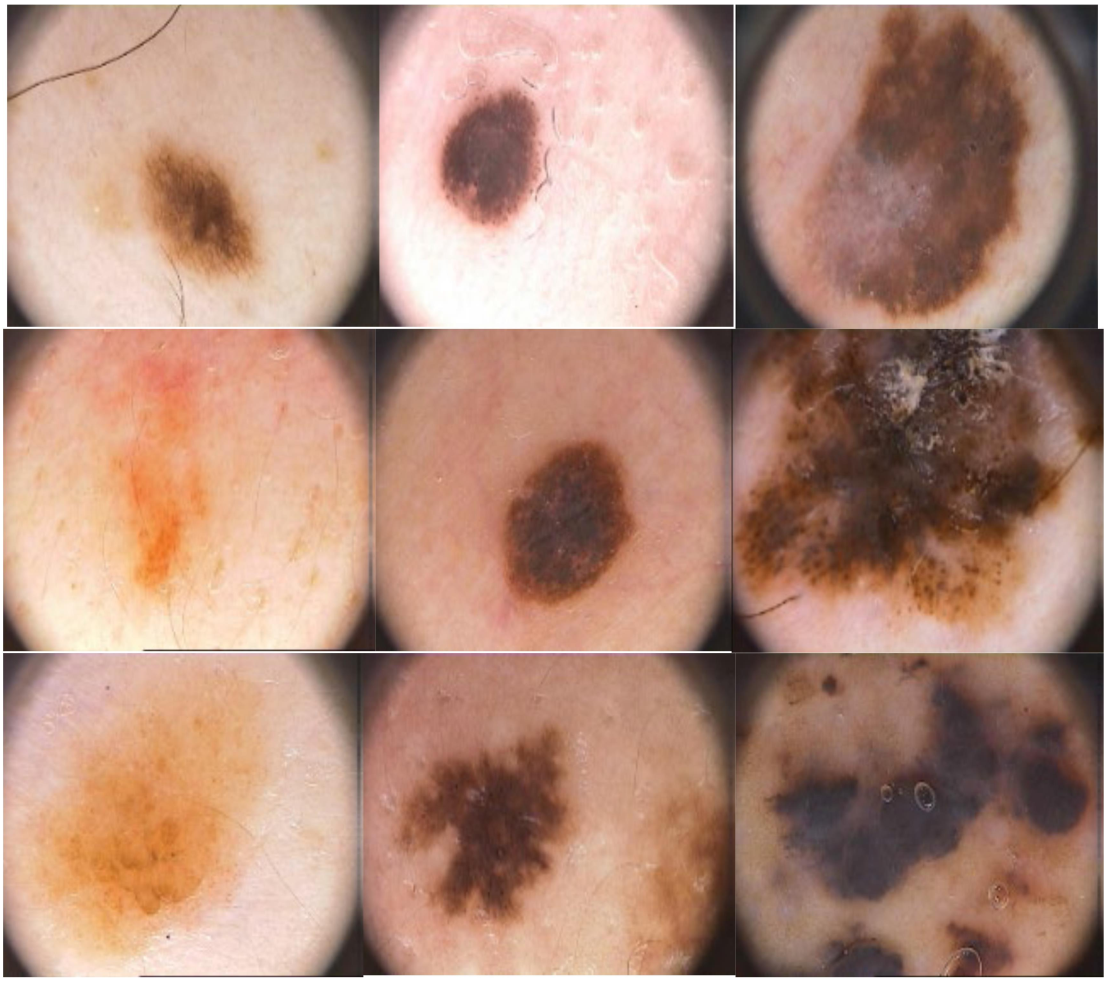
Baştürk et al., Deep Neural Network (DNN), an innovative technique for detecting melanoma skin cancers, was utilised in their research, and they achieved an accuracy of 91.85% in disease diagnosis using this technique [18].

Proposed Work

A. Dataset

Using the machine learning algorithms that were developed for the purpose of melanoma diagnosis, a diagnostic research was carried out on the PH2 data set. A team of researchers from the Technical Universities of Porto and Lisbon worked together with the dermatological service at Pedro Hispano

Hospital to compile this data collection. The PH2 dataset includes 200 dermoscopy pictures with dimensions of 768 x 560 pixels each. Every picture has RGB channels that are each 8 bits [16].



Normal B. Abnormal C. Malenon

Fig 1: Views of the sample lesions in the PH2 data set

There are a total of 80 photos available for the normal type, 80 images available for the abnormal type, and 40 images available for the melanoma type inside the PH2 data set. Figure 1 displays several instances of these for your reference. In spite of the fact that the PH2 data set was constructed by extracting the characteristics in accordance with the criteria outlined in the ABCD rule, the criterion B was disregarded in this instance. Because of this, the characteristics discovered in the dataset and used in the research were:

Within the context of this investigation, the dermoscopic pictures of the data sets served as the basis for four distinct classification approaches that were applied to the skin lesions. In the next paragraphs, brief information regarding each of the classifying approaches, namely ANN, SVM, KNN, and DT, will be presented.

The acronym ANN stands for artificial neural network. ANNs, or artificial neural networks, are mathematical systems that are made up of multiple process units (neurones) that are weightily coupled with each other. The process unit is responsible for collecting the signals sent by other neurones, combining and transforming those signals, and producing a numerical output. In a broad sense, the process units approximately correspond to actual neurones and are joined in a network to form what are known as artificial neural networks [19]. This structure is what makes up the artificial neural networks.

SVM: Support vector machines are a kind of nonparametric classifier. There is currently no preliminary information that can be used as a basis for a presumption about their dispersion. Within the training sets, inputs and outputs are coupled together. It is possible to generate decision functions that categorise the input variables in both the test set and the new data set by means of the pairs. The job at hand is to be able to identify, out of the infinite number of lines that are capable of classifying the data, the line that has the biggest margin in situations when linear separation is feasible. When a linear separation wouldn't work, it transforms the data from the original work into a higher dimension using a non-linear mapping. This is done when it would be impossible to separate the data linearly. In the newly converted dimension, an investigation is being conducted to determine the (optimal) separator plane that has the greatest margin [20].

K-Nearest Neighbour (KNN): One of the most fundamental examples of a sample-based learning algorithm is known as the KNN algorithm (K-Nearest Neighbour). In algorithms for learning based on examples, the learning process is carried out based on the information that is included in the training set. A newly presented example is classified based on the degree to which it resembles other instances in the currently accessible training set.

Decision tree (DT): The decision tree is a classifier algorithm in the structure form of a “tree”. Decision Trees are simple, but very commonly used methods by moving the inductive logic into a programming environment. It works with discrete valued parameters. The basic intuition about the inductive philosophy on which the decision tree algorithms are based is that a “good” decision tree to be constructed with learning characteristics should be small as possible.

Result Discussion

Artificial Neural Network (ANN), Support Vector Machine (SVM), K-Nearest Neighbours (KNN), and Decision Tree (DT) classifiers were compared with each other inside a PH2 data set in this research for the purpose of diagnosing melanoma. "one-of-N coding" is used for encoding categorical values in this study's entries that are carried out by participants.

The findings of the empirical study indicated that the ideal value for "k" in the k-fold cross-validation technique fell somewhere in the range of 5 to 10. Experiments were performed, and the results established this. During the course of this study endeavour, a 10-layer cross-validation methodology was used, which led to the data set being divided up into ten distinct sections as a consequence. The system is taught and tested by using "k" separate training and test clusters, and for each scenario, "k" different performance measures are achievable. As a result, the arithmetic mean of the "k" performance measurements that were gathered is calculated in order to determine whether or not the cross validation was successful.

Throughout the course of this investigation, the functions that can be located in the MATLAB Statistics and Machine Learning Toolbox as well as those that can be discovered in the MATLAB Neural Network Toolbox were used [28, 29]. The freshly formed ANN structure has the potential to be partitioned into three separate layers. Each of the twelve input parameters that are included inside the data set is responsible for determining the input vector that is used at the Layer 1 level. Layer 3 is the layer that represents the result of the classification, and the total number of classes that were represented in the output was used to calculate the number of neurones that were included in this layer of the network. The scaled conjugate gradient back propagation method is the name of the learning technique that is used.

On the basis of the provided network structure, a range of network topologies with anywhere from 2 to 50 neurones were trained in order to determine the number of neurones in the hidden layer that produced the most accurate results. After looking at the previously established network topologies in the research, the authors decided to employ the ANN design with 18 neurones in the hidden layer since it had the highest accuracy (92.50%).

According to Table 1, ANN has an accuracy of 92.50%, whereas SVM has an accuracy of 89.50%, KNN has an accuracy of 82.00%, and DT has an accuracy of 90.00%. It would seem from this that the suggested ANN has a classification performance that is noticeably superior when applied to the PH2 data set. In Table 1, the accuracy values of the ANN, SVM, KN, and DT algorithms for each classifier output are shown for the purpose of the classification of skin lesions according to the data from the PH2 data set. These algorithms were used to analyse the data. It would indicate that the ANN classifier is more effective than other algorithms when it comes to correctly diagnosing each skin lesion.

Table 1: Machine learning Algorithms Values

Algorithms	Accuracy	Balance Accuracy	Sensitivity	Specifity	Precision	F1-Score
ANN	92.50	93.49	90.86	96.11	92.38	90.45
SVM	89.50	90,35	86.25	94.44	89.09	87.31
KNN	82.00	85,04	79.58	90.49	81.45	80.33
DT	90.00	90,97	87.08	94.86	88.58	87.70

1. Accuracy

In addition to this, we checked out the data for both the test score and the train score. In order to get the best performance values that can be obtained for each classifier, extensive testing was performed on a large number of parameter combinations.

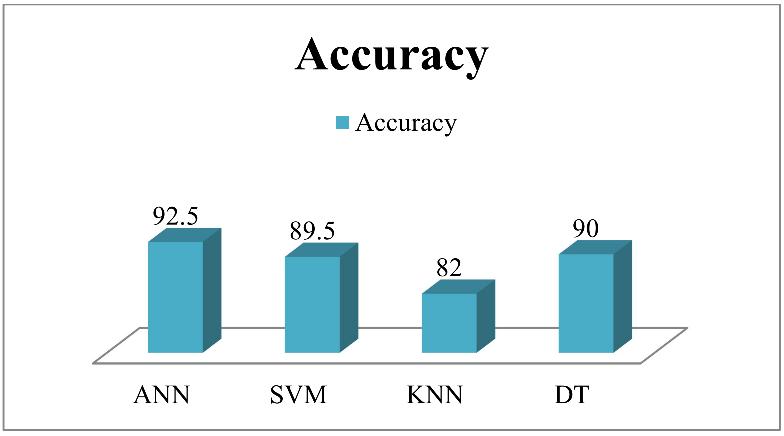


Fig 2: Comparison Accuracy of Machine learning algorithms

2. Precision

The fraction of retrieved instances those are relevant.

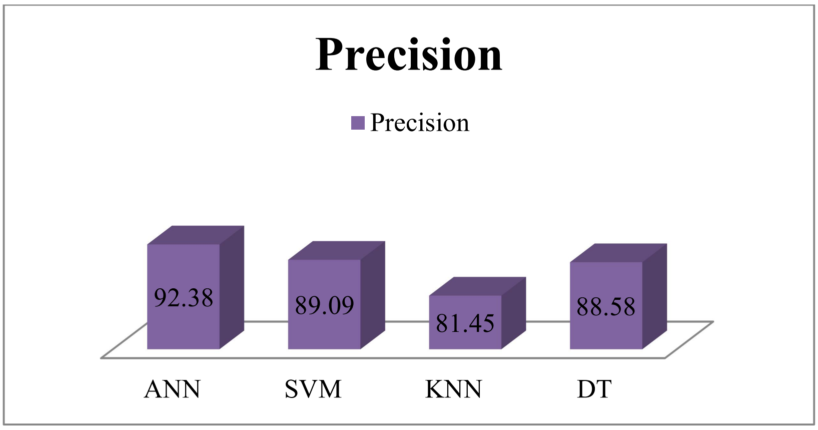


Fig 3: Comparison Precision of Machine learning algorithms

F1- Score

The F- measure also refers to F measures that combined both the measures Precision and Recall as the harmonic mean.

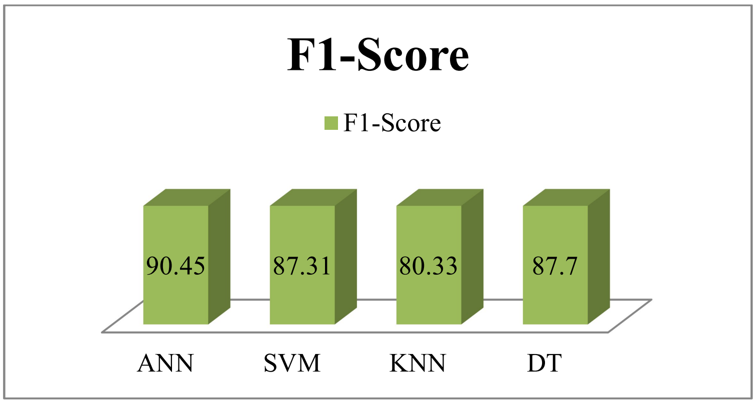


Fig 4: Comparison F1-Score of Machine learning algorithms

Conclusion

Within the scope of this study, machine learning techniques are used in order to diagnose a variety of skin conditions. The early diagnosis of skin diseases is critical for lowering the mortality rate. When compared to machine learning, the dermatological technique for determining the kind of skin illness is quite expensive.

Combining image processing methods with machine learning assists in making an accurate diagnosis of the condition. When it comes to identifying skin disorders, feature selection is an extremely significant factor. Entropy and variance are used as textural characteristics in the construction of decision trees in this body of work. The fact that the ANN classifier was able to attain an accuracy of 92.50% demonstrates that this classifier is a medical decision support system that might assist dermatologists in correctly diagnosing skin lesions.

It is possible to make additional progress with this research by using the various strategies for preliminary data processing and hybrid classification algorithms. This research, in addition, may be integrated with the relevant image processing methods in order to achieve the capability of making independent judgements on a variety of medical concerns.

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