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Predictive Modelling for Skin Disease Classification Using Machine Learning

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Abstract:

Skin diseases are among the most common health conditions worldwide. However, diagnosing them accurately is often challenging due to the complex nature of skin—its texture, color variations, and the presence of hair can all interfere with proper analysis. To enhance diagnostic accuracy, especially across various skin types, there is a growing need to develop advanced methods that incorporate machine learning. Machine learning has become a widely used tool in medical diagnostics, offering promising results in identifying skin-related conditions. In this approach, the algorithm processes images of skin diseases and goes through three main stages: feature extraction, training, and testing. By using large datasets of skin images, the system can effectively train itself to recognize different skin conditions. The goal of this process is to improve the accuracy of skin disease classification. Key visual elements such as texture, color, and shape play a critical role in distinguishing between healthy and diseased skin. In particular, this study focuses on using color groupings to classify skin conditions. The color of healthy skin differs noticeably from that of affected areas. Similarly, the texture of the skin—whether it's smooth, rough, or patterned—can help in identifying abnormalities. For an effective diagnosis, the study investigates two main types of image features: texture and color. Specific metrics like entropy, variance (dispersion), and HSV (Hue, Saturation, Value) color histogram peaks are used to extract these features. These features are then analyzed using Decision Trees (DT) and Support Vector Machines (SVM), two popular machine learning algorithms.

Keywords — Image processing, Skin diseases, Machine learning, Feature extraction

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1. INTRODUCTION

Artificial Intelligence (AI) is rapidly transforming industries around the world, and healthcare is no exception. In recent years, the sudden emergence and complex nature of certain skin diseases have raised serious concerns due to the significant risks they pose to human health. Many of these skin conditions are highly contagious, making timely

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and accurate diagnosis critical to preventing their spread.

A major cause of these illnesses is prolonged, unprotected exposure to ultraviolet (UV) radiation from the sun. Among them, malignant melanoma is particularly dangerous and more challenging to treat compared to benign melanoma, which generally carries a lower risk and fewer complications. Because of the urgency and potential severity of such conditions, the integration of AI-driven technologies into dermatological diagnosis is becoming increasingly important.

Among all types of skin cancer, malignant melanoma is considered the most dangerous. Research shows that it most commonly develops on areas such as the back, lower limbs, trunk, and upper limbs. The disease is most frequently diagnosed in individuals aged 30 to 60 years, making this age group the most vulnerable. In contrast, certain skin conditions like melanocytic nevi, carcinomas, and dermatofibromas are quite rare in people under the age of twenty.

To aid in the detection and prediction of such conditions, Artificial Neural Networks (ANNs) have become a powerful tool. ANNs are statistical models designed to learn and map complex relationships between input data (such as skin images) and output classifications (such as disease type). Their structure is inspired by the biological neurons found in the human brain, allowing them to simulate how the brain processes and analyzes information in a highly efficient, non-linear manner.

In an Artificial Neural Network (ANN), each node (or neuron) performs computations in one of three ways. These networks learn through a method known as backpropagation, where the model adjusts its internal parameters based on the errors it makes during training. Datasets used in this learning process are categorized as either trained (labeled) or untrained (unlabeled).

For trained datasets, ANNs typically use supervised learning, which allows the network to learn patterns based on labeled inputs and expected outputs. For untrained datasets, unsupervised learning techniques are used, where the model identifies hidden structures without explicit labels. Different neural network architectures, such as feedforward networks or backpropagation-based models, process the data in distinct ways to improve accuracy.

However, despite advancements, the accuracy of Convolutional Neural Networks (CNNs) used in skin disease detection often peaks around 80%, which indicates room for improvement. Additionally, ANNs demand significant computational power, typically requiring multi-core, parallel-processing CPUs. One major limitation of ANNs is their lack of interpretability—they can generate predictions but often fail to explain why or how those predictions were made, which can undermine trust in their results.

On the other hand, the Support Vector Machine (SVM) offers an alternative supervised learning method. SVM is a non-linear classifier that creates an optimal n-dimensional hyperplane to separate data points into two distinct categories. While effective, SVMs come with their own challenges. Choosing an appropriate kernel function—which plays a crucial role in performance—is not straightforward. Moreover, training on large datasets can be time-consuming, and the resulting model can be difficult to interpret or fine-tune. Despite these issues, SVMs have shown to consistently outperform ANNs in terms of accuracy across various classification tasks.

2. Literature Survey

Skin diseases rank as the fourth most common cause of global health burden. To help ease this burden and support early evaluation of skin lesions, a reliable and automated diagnostic method has been proposed. Most existing approaches in the literature are primarily focused on skin cancer,

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limiting their applicability to other common skin conditions. Early detection significantly improves treatment outcomes and reduces the risk of disfigurement, yet research in this area remains challenging due to the visual similarities among various skin disorders. This study introduces a novel method for diagnosing several common skin lesions, including melanocytic nevi, melanoma, benign keratosis-like lesions, basal cell carcinoma, actinic keratoses, vascular lesions, and dermatofibroma. The proposed method involves a structured pipeline consisting of image pre-processing, implementation of a deep learning algorithm, training of the model, validation, and final classification. By addressing multiple types of lesions, this approach aims to enhance diagnostic accuracy and offer a more comprehensive solution for skin disease identification.

Experiments were conducted on a dataset of 10,010 images, and the results demonstrated that Convolutional Neural Networks (CNN) integrated with the Keras Application Programming Interface achieved an impressive 93% accuracy in seven-class skin lesion classification. Traditional diagnostic approaches, such as the ABCD rule-based method and computer-aided systems, have also shown potential in significantly improving melanoma detection accuracy. These systems generally consist of separate modules for image segmentation, feature extraction, and classification.

Notable research in this field includes several studies. Baldrick et al. compared expert dermatologist evaluations with artificial neural network outcomes, achieving a sensitivity of 95% and specificity of 88% from the computer program, closely matching the expert assessments of 95% sensitivity and 90% specificity. Moataz et al. applied a genetic algorithm along with an artificial neural network for early skin cancer diagnosis, achieving a sensitivity of 91.67% and a specificity of 91.43%. Kamasak et al. employed Fourier ID extraction from lesion edges after segmenting dermoscopic images, reaching an accuracy of 83.33% in melanoma detection. Fidan et al. developed a neural network specifically tailored for melanoma and atypical skin cancers, achieving a success rate of 93.33% using data from the PH2 dataset. Lastly, Baştürk et al. utilized a Deep Neural Network (DNN) for melanoma detection, reporting an accuracy of 91.85% in their diagnostic model.

These findings collectively highlight the strong potential of deep learning and hybrid AI approaches in improving the early detection and classification of skin diseases, especially melanoma.

3. PROPOSED WORK

A diagnostic study was conducted using machine learning algorithms specifically developed for melanoma detection, based on the PH2 dataset. This dataset was compiled through a collaborative effort between researchers from the Technical Universities of Porto and Lisbon and the dermatology department of Pedro Hispano Hospital. The PH2 dataset contains a total of 200 dermoscopic images, each with a resolution of 768 x 560 pixels. These images are stored in RGB format, with each color channel represented by 8-bit values, making the dataset suitable for high-quality image analysis and feature extraction in melanoma research.

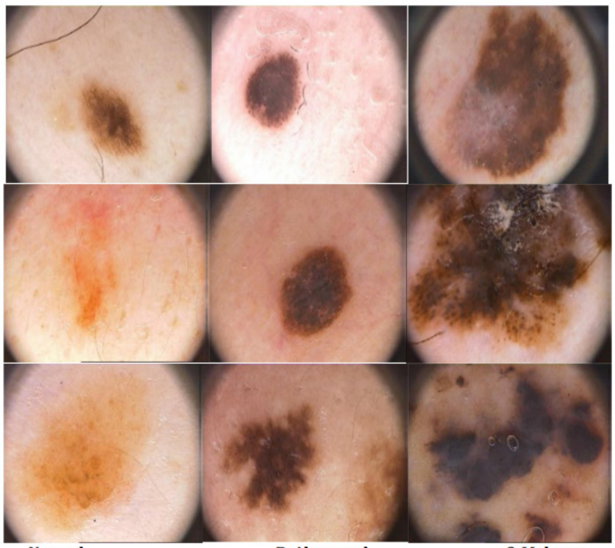

Fig 1: Views of the sample lesions in the PH2 data set

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The PH2 dataset consists of a total of 200 dermoscopic images, categorized as follows: 80 images of normal skin lesions, 80 images of abnormal (but non-melanoma) lesions, and 40 images of melanoma cases. Examples of each category are illustrated in Figure 1 for reference. Although the PH2 dataset was originally developed using feature extraction based on the ABCD rule—a commonly used method for melanoma assessment—criterion B (border irregularity) was excluded from this analysis. As a result, only selected characteristics from the dataset were utilized in the study.

In this investigation, the dermoscopic images served as the foundation for applying four distinct machine learning classification algorithms to detect and classify skin lesions. These algorithms include Artificial Neural Networks (ANN), Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Decision Trees (DT). The following sections briefly introduce each of these classification approaches and their role in enhancing diagnostic accuracy.

The acronym ANN stands for Artificial Neural Network. ANNs are mathematical models composed of numerous interconnected processing units, commonly referred to as neurons. Each neuron receives input signals from other neurons, combines and transforms these signals through a weighted mechanism, and generates a numerical output. Conceptually, these processing units are designed to mimic the behavior of biological neurons, and when connected together in a structured network, they form what is known as an artificial neural network. This network architecture enables the ANN to learn complex patterns and relationships within data, making it a powerful tool in tasks such as classification, prediction, and pattern recognition.

SVM, or Support Vector Machine, is a type of non-parametric classifier, meaning it does not rely on prior assumptions about the distribution of the data. In SVM, the training dataset consists of paired inputs and outputs, which are used to create decision functions capable of classifying both test data and unseen data.The central objective of SVM is to find the optimal separating hyperplane—among the infinite possibilities—that offers the maximum margin between classes, particularly in cases where a linear separation is feasible. However, when the data is not linearly separable, SVM employs a non-linear mapping technique to transform the original data into a higher-dimensional space. In this transformed space, the algorithm searches for a new hyper plane that can linearly separate the data with the widest possible margin. This approach allows SVM to handle complex classification tasks with high accuracy.

K-Nearest Neighbour (KNN) is one of the most fundamental and widely used instance-based learning algorithms. In KNN, the learning process relies entirely on the data present in the training set, without building an explicit model during training. When a new, unknown instance is presented, the algorithm classifies it by comparing it to the K most similar instances (neighbors) in the training data. The classification is then determined based on the majority class among these neighbors, making KNN a similarity-based and intuitive approach to classification. Decision Tree (DT) is a tree-structured classification algorithm that makes decisions by following a series of rules derived from the input data's features. Each internal node in the tree represents a test on an attribute, each branch corresponds to an outcome of the test, and each leaf node represents a class label. Decision trees operate on discrete-valued attributes and use inductive logic to learn patterns from the data. The key idea behind decision trees is to construct a model that is as simple and small as possible while still accurately capturing the relationships in the data—this follows the principle of Occam’s razor, which favors simpler models that generalize well.

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4. RESULT DISCUSSION

In this study, Artificial Neural Network (ANN), Support Vector Machine (SVM), K-Nearest Neighbours (KNN), and Decision Tree (DT) classifiers were compared using the PH2 dataset for the purpose of diagnosing melanoma. To handle categorical values in the dataset, the study employed a technique known as "one-of-N coding", which encodes categorical data into a binary format suitable for machine learning algorithms. The research applied k-fold cross-validation to evaluate model performance, and experimental findings indicated that the optimal value for "k" lies between 5 and 10. For consistency and robustness, the study specifically used a 10-fold cross-validation approach. In this method, the dataset was divided into ten equal parts, and in each round, one part was used for testing while the remaining nine parts were used for training. This process was repeated ten times, allowing every section to serve as a test set once.For each fold, performance metrics were recorded, and the arithmetic mean of these k performance measures was calculated. This averaging method ensures that the evaluation reflects the model's generalization ability, providing a more reliable estimate of its true performance on unseen data.In this study, the classification models were implemented using functions from the MATLAB Statistics and Machine Learning Toolbox and the MATLAB Neural Network Toolbox [28, 29]. The newly designed Artificial Neural Network (ANN) structure was organized into three distinct layers:

- Layer 1 is the input layer, which processes the input vector composed of twelve parameters extracted from the dataset. Each of these parameters contributes to forming the input vector fed into the network.
- Layer 3 is the output layer, which represents the final classification result. The number of neurons in this layer corresponds to the number of target classes, allowing the network to distinguish among all possible skin disease types in the dataset.

The learning algorithm used to train the network is the Scaled Conjugate Gradient Backpropagation method. This training technique is known for its efficiency in handling complex and high-dimensional data, making it well-suited for tasks such as medical image classification.

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

A. Accuracy

In addition to this, we checked out the data for both the test score and the train score. In order to get the 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%).

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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. best performance values that can be obtained for each classifier, extensive testing was performed on a large number of parameter combinations.

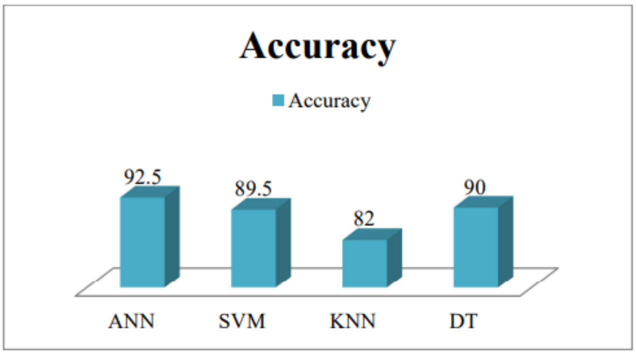

Fig 2: Comparison Accuracy of Machine learning algorithms

B. Precision

Precision is a performance metric used to evaluate the accuracy of a classification or retrieval system

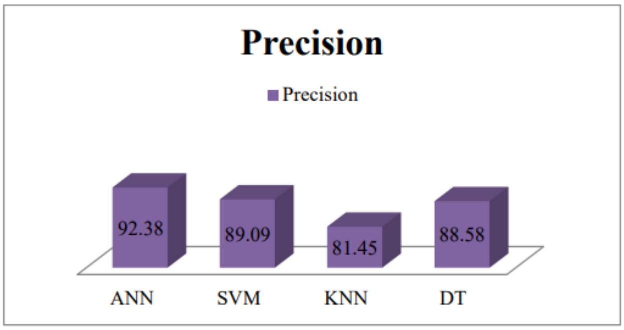

Fig 3: Comparison Precision of Machine learning algorithms

C. F1- Score

The F-measure, also known as the F1-score, is a metric that combines both Precision and Recall into a single value by calculating their harmonic mean. It is especially useful when you need a balance between precision and recall, and when there is an uneven class distribution.

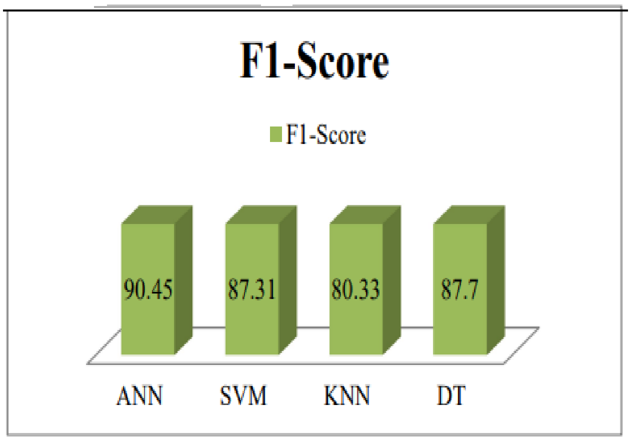

Fig 4: Comparison F1-Score of Machine learning algorithms

5. Conclusion

In this study, machine learning techniques are explored as a way to diagnose various types of skin conditions more efficiently and accurately. Early detection of skin diseases is extremely important, as it plays a vital role in reducing the risk of severe complications and even lowering mortality rates. Traditional dermatological methods, while effective, can often be costly and time-consuming. In contrast, machine learning offers a faster, more affordable alternative that can support early diagnosis and improve patient outcomes.

Combining image processing techniques with machine learning plays a crucial role in accurately diagnosing skin conditions. One of the most important steps in this process is feature selection, which directly impacts the effectiveness of the diagnosis. In this study, entropy and variance are used as key textual features to help construct decision trees that support classification.Notably, the Artificial Neural Network (ANN) classifier achieved an impressive 92.50% accuracy,

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highlighting its potential as a valuable medical decision support system. Such a system can assist dermatologists in making more accurate and faster diagnoses of skin lesions.Looking ahead, the research can be further enhanced by incorporating more advanced data preprocessing techniques and combining multiple classification algorithms (hybrid models). Additionally, integrating this work with modern image processing methods could eventually lead to intelligent systems capable of making autonomous medical decisions in various diagnostic scenarios.

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