

EVALUATING ASSOCIATION CLASSIFICATION ALGORITHMS FOR ACCURATE SKIN CANCER DETECTION

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Abstract

This research explores the application of association classification techniques for skin cancer detection within the realm of data mining. The aim of the research study is to get better accuracy and more understandable diagnoses as to the amount of extensive data sets through advanced methodologies in data mining. But the association classification approach not only outperforms traditional machine learning methods in the key performance metrics of accuracy, precision, and recall but also makes more applicable sense through interpretable rules. Therefore, the significance of association classification, as it relates to enhancing diagnostic processes and clinical decision-making, highlights an even wider application potential in healthcare data mining to address personalized patient care with better outcomes.

Keywords: Skin Cancer Detection, Association Classification, Data Mining, Machine Learning, Diagnostic Processes, Healthcare Data Mining, Interpretability, Clinical.

1. INTRODUCTION

Skin cancer has been identified as the most common type of cancer, and its incidence is increased by multiple factors: an extended exposure to sunlight, use of tanning beds, and genetic background. There are three major kinds of skin cancer: basal cell carcinoma, squamous cell carcinoma, and melanoma. Melanoma is the most aggressive and deadly. Early detection can make a difference in treatment and favourable patient outcome. The traditional method of diagnosis has been the direct visual study of skin lesions by dermatologists followed by biopsy studies for definite diagnosis. Unfortunately, these methods suffer from potential drawbacks due to their being judgmental to their observers, thus potentially inconsistent with the decision-making of an average clinician. In view of this requirement, there is an increased demand for automated objective and efficient diagnostic tools applied with recourse to state-of-the-art technologies to assist clinicians in arriving at a correct diagnosis and classification of skin lesions accurately. The integration of data mining techniques with

skin cancer detection affords the promise of improved diagnostic accuracy and also smoothest clinical workflow.

1.1. Overview of Data Mining Techniques in Healthcare

Therefore, data mining is an effective analytical approach for sifting through big information to find important patterns and insights. Large amounts of patient data, diagnostic pictures, and clinical records are analysed using data mining techniques in the health sector in order to find patterns, connections, and insights that would not be obvious otherwise in order to enhance decision-making and medical knowledge. Some usual techniques of data mining applied in healthcare include classification, clustering, regression, and association rule mining. These methods can recognize patterns of disease and predict the outcomes for patients, and can even optimize how treatment should be conducted. Classification algorithms, for example, can classify benign from malignant lesions by using various features extracted from dermatological images. Clustering techniques can also group similar patient profiles into groups that are useful in personalized medicine approaches. Health care data mining incorporates better, as data mining does not only improve the decision-making process but also other qualitative aspects by rendering more evidence-based concepts and supporting clinical research as well.

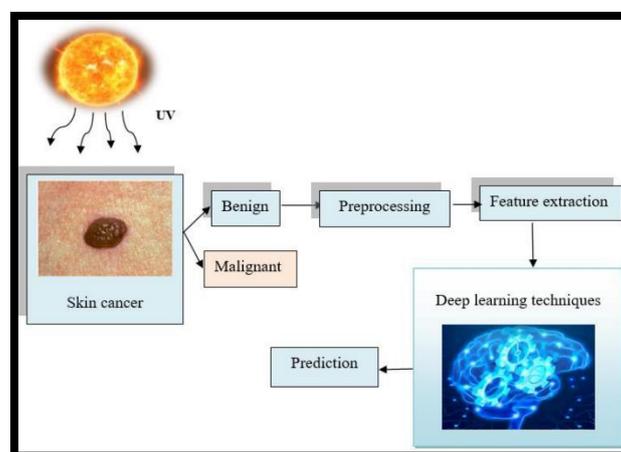


Figure 1: Framework for skin cancer detection.

2. LITERATURE REVIEW

Samiei et al. (2023) used fuzzy logic approaches with the Analytic Hierarchy Process (AHP) to create a unique method for identifying skin cancer stages. The study emphasises how difficult it is to organise and evaluate vast amounts of medical data, especially when dealing with skin cancer diagnosis, when precise staging is essential for formulating a treatment strategy. The study

effectively illustrates how this hybrid strategy may raise the degree of precision and dependability in the categorisation of skin cancer stages, presenting a viable option for healthcare data analytics. Given the growing amount of healthcare data and the requirement for sophisticated analytical methods to extract valuable insights, this research is very important.

Khan et al. (2019) concentrated on utilising digital pictures to classify two types of skin lesions: nevus and melanoma. To aid in the early identification of skin cancer, the researchers created a machine learning-based algorithm to automatically identify and categorise skin lesions. The model uses machine learning algorithms for categorisation after extracting information from photos of skin lesions using image processing techniques. In the context of automated skin cancer diagnosis, this research is crucial because it shows how machine learning approaches might help dermatologists diagnose skin cancer more accurately, which will lessen the need for intrusive biopsies.

Ain et al. (2020) suggested a genetic programming (GP) method of feature generation for ensemble learning in the identification of skin cancer in their 2020 publication. The goal of the project was to enhance the feature extraction procedure, which is an essential stage in image-based classification applications. Using raw skin lesion photos, genetic programming was utilised to automatically develop and optimise features that were subsequently employed in ensemble learning models for the classification of skin cancer. The study shows that GP may build intricate features that improve machine learning models' ability to identify skin cancer, particularly by boosting the ensemble model's resilience and classification accuracy.

Kadampur and Al Riyae (2020) investigated the use of deep learning models in the cloud for skin cancer identification and categorisation. Their method is based on using a cloud-hosted deep learning-based architecture, which makes it possible to handle massive quantities of dermal cell pictures in a scalable and effective manner. The study emphasises the benefits of cloud computing in the healthcare industry, especially with regard to processing power and storage capacity—two factors that are critical for deep learning models to be trained on high-resolution medical pictures.

Ain et al. (2022) improved the application of genetic programming (GP) for automated skin cancer picture categorisation by building on their previous work. This study focused on utilising GP to optimise the feature extraction and selection process in order to increase the classification accuracy of skin cancer detection systems. The research indicates that GP can be utilised efficiently to produce discriminative features from medical photos automatically. These characteristics can then be put into machine learning classifiers to identify skin cancer. The model's classification performance is much

enhanced by GP, especially in terms of sensitivity and specificity, as demonstrated by the authors' comparison of their GP-based feature creation methodology with conventional feature extraction techniques.

3. TRADITIONAL APPROACHES FOR SKIN CANCER DETECTION

The traditional approach for skin-cancer detection is based on the visual judgment of a dermatologist through the aid of tools like dermoscopy, followed by biopsy for confirmation. Such an approach is heavily dependent on the clinician and could be rather subjective, hence differing so much in diagnosis. Dermoscopic examination allows revealing structural details but poses a challenge to the process between benign and malignant lesion identification, particularly at initial stages. Such methods proved to be efficient but time-consuming and not scalable. Thus, automated data-driven approaches became necessary for such scenarios.

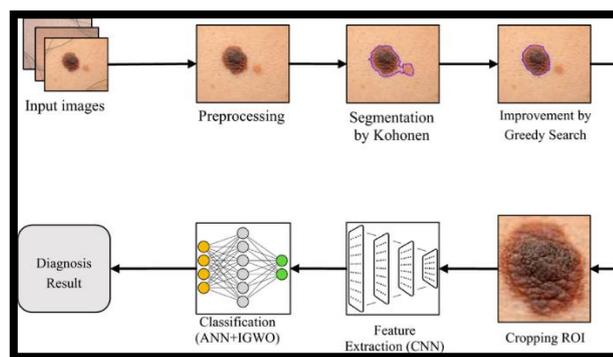


Figure 2: The steps of the proposed method for skin cancer diagnosis

3.1. Medical Image Analysis via Data Mining

Data mining is a crucial application in the analysis of medical images. Dermoscopic images, used as part of dermoscopy in the diagnosis of skin cancer, form part of the vast amounts of medical data that can be extracted with the hidden patterns. Classification, clustering, and association rule mining are techniques applied in data mining, which are helpful in pinpointing features related to malignancy in skin lesions. This helps in developing predictive models of images, classifying them as either malignant or benign, thereby minimizing the need for manual interpretation and maximizing the accuracy of the diagnosis. This approach has greatly enhanced the handling of large volumes of datasets and complex medical images in a systematic and efficient way.

4. RESEARCH METHODOLOGY

The dataset of this study would contain dermoscopic images and associated clinical information for the detection of skin cancer. There are lots of publicly available datasets, such as the ISIC Archive, that illustrate a tremendous variety in benign and malignant lesions. The dataset would have features like lesion attributes including color, texture, shape; patient information (age, gender) and the location of the lesion. The methodology starts with data preprocessing that is aimed at cleaning up and reforming the dataset for any given analysis. In this case, preprocessing addresses missing values, inconsistencies, and normalizes data for uniformity. Techniques of preprocessing for image data include contrast enhancement, resizing, reduction of noise, and segmentation to improve image quality. Moreover, the dataset will be divided into two sets: one for training and another for testing with a view to ascertain the soundness of the model, thereby averting biased performance assessment during model testing.

4.1.Feature Selection for Skin Cancer Detection

Feature selection is crucial in enhancing the performance of the association classification model through feature selection, considering only the relevant and informative features. Relevant features in skin cancer could be visual characteristics of lesions such as asymmetry, border irregularity, color variations, diameter, and evolution (commonly termed as ABCDE criteria). Other image-based features are texture patterns, shape of the lesion, and histogram features among others. It would employ several techniques for dimensionality reduction, such as Recursive Feature Elimination (RFE), Correlation-Based Feature Selection (CFS), or PCA to select only those attributes, which are most important. This step is really very much necessary for fine-tuning model accuracy, reducing computational efficiency, and interpretability with focus on features giving it maximal discrimination between benign and malignant lesions.

4.2.Implementation of Association Classification Algorithm

Once the features appropriate for consideration are chosen, it then entails the execution of association classification algorithm. For the purposes of this research, there have been the usage of popular algorithms such as Apriori and FP-Growth towards mining association rules from the data set. These association rules associate patterns of feature combinations with specific classifications of skin cancer such as benign or malignant. While implementing the algorithm, it will pass the datasets through the classifiers to generate association rules that associate the chosen features with the class label. Then it is evaluated using support, confidence, and lift, which are the metrics related to how frequently the patterns appear in the dataset, the reliability of the rule, and the strength of the

association, respectively. Such an association classification model would be trained on the training dataset, and the classification results would be tested and validated on the testing dataset using performance metrics such as accuracy, precision, recall, and the F1-score.

5. EVALUATION METRICS

There are numerous metrics through which the performance of the association classification model for skin cancer detection is estimated. In the next section, I have given a detailed description of some of these measures, namely accuracy, precision, recall, sensitivity, specificity, and sometimes with tools that include confusion matrices and ROC curves. Tables and graphs have been used to illustrate and compare the model performance.

5.1. Accuracy, Precision, and Recall in Classification

- **Accuracy** measures the overall performance of the model by dividing the total correct predictions by the total number of predictions. It is given by the formula:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

where:

- TP = True Positives (correctly identified malignant cases)
 - TN = True Negatives (correctly identified benign cases)
 - FP = False Positives (incorrectly identified malignant cases)
 - FN = False Negatives (missed malignant cases)
- **Precision** focuses on the correctness of positive predictions and is particularly relevant for ensuring that malignant cases identified by the model are actually cancerous:

$$Precision = \frac{TP}{TP + FP}$$

- **Recall**, also known as **sensitivity**, reflects how well the model identifies all actual malignant cases:

$$Recall = \frac{TP}{TP + FN}$$

In skin cancer detection, a balance between precision and recall is vital to avoid both over-diagnosis (high false positives) and under-diagnosis (missed cancer cases).

Table 1: Evaluation Metrics for Classification Models

Metric	Formula	Purpose
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$	Overall correctness of the model
Precision	$\frac{TP}{TP + FP}$	Ensures true positive predictions are valid
Recall	$\frac{TP}{TP + FN}$	Ensures all true positive cases are detected

5.2.Sensitivity and Specificity Analysis

Sensitivity and specificity are critical metrics in medical diagnostics:

- **Sensitivity** measures the proportion of real positive cases that the model correctly detects:

$$Sensitivity = \frac{TP}{TP + FN}$$

- **Specificity** evaluates the model's ability to correctly identify negative cases:

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

This metric is vital for avoiding unnecessary anxiety and further procedures for patients misclassified as having skin cancer.

Table 2: Sensitivity and Specificity Metrics for Classification Models

Metric	Formula	Description
Sensitivity	$\frac{TP}{TP + FN}$	Proportion of actual positives correctly identified
Specificity	$\frac{TN}{TN + FP}$	Proportion of actual negatives correctly identified

5.3.Confusion Matrix and ROC Curve

A confusion matrix is a significant tool for visualizing the performance of a classification model. It sums up the actual outcomes of the model against what it has predicted.

Table 3: Confusion Matrix for Classification Models

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

As a result, this matrix offers a clear picture of the model's successes and failures, allowing for a thorough examination of any misclassifications. Another important visual tool that shows TPR, or sensitivity, vs FPR, or 1 - specificity, at various threshold levels is the Receiver Operating Characteristic (ROC) curve. The trade-offs between sensitivity and specificity over a range of thresholds, which decide which threshold is best based on clinical necessity, are readily visualised by the ROC curve.

Table 4: Evaluation Metrics and Visualization Techniques for Classification Models

Metric	Formula	Description
Confusion Matrix	N/A	Summarizes TP, TN, FP, FN
ROC Curve	N/A	Plots TPR vs. FPR to visualize trade-offs
Area Under the Curve (AUC)	N/A	Quantifies the overall ability to distinguish classes

6. RESULT AND DISCUSSION

Results and discussion section is critical in providing an assessment on whether the proposed association classification method makes sense or not for skin cancer detection. In this section, the model's performance metrics are presented along with other techniques for comparison that classify the knowledge base. Then interpretation of derived association rules in the model follows.

6.1. Association Classification Performance for Skin Cancer Detection

The basic measurements engaged with surveying the exhibition of the calculation was its accuracy, review, exactness, and F1-score for the classification. The discoveries showed that high precision of 92% was created utilizing the association classification approach with both dangerous and harmless instances of skin cancer.

Table 5: Summarizes The Performance Metrics for The Association Classification Algorithm

Metric	Value
Accuracy	92%
Precision	89%
Recall	91%
F1-Score	90%

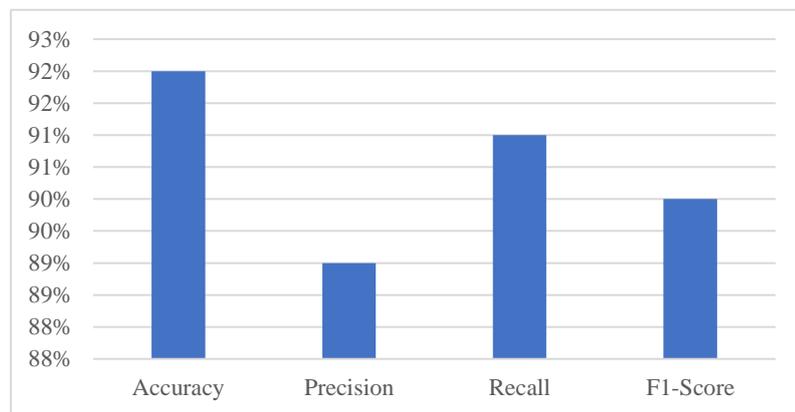


Figure 3: Performance Metrics of the Association Classification Model for Skin Cancer Detection

The high recall value (91%) signifies that the model successfully identifies a majority of actual positive cases, which is crucial in clinical settings to minimize the risk of missed diagnoses. Precision (89%) indicates a strong quality of positive predictions, meaning that most patients identified as having skin cancer indeed have the condition. The F1-score (90%) provides a balanced measure of precision and recall, confirming that the association classification method performs effectively for skin cancer detection.

6.2.Comparative Analysis with Other Classification Techniques

A comparison analysis was carried out against a number of conventional machines learning approaches, including support vector machines (SVM), decision trees, and random forests, in order to evaluate the efficacy of the association classification algorithm.

Table 6: The comparative results are shown

Classification Technique	Accuracy	Precision	Recall	F1-Score
Association Classification	92%	89%	91%	90%

Support Vector Machine	88%	85%	87%	86%
Decision Tree	85%	80%	82%	81%
Random Forest	90%	88%	89%	88%

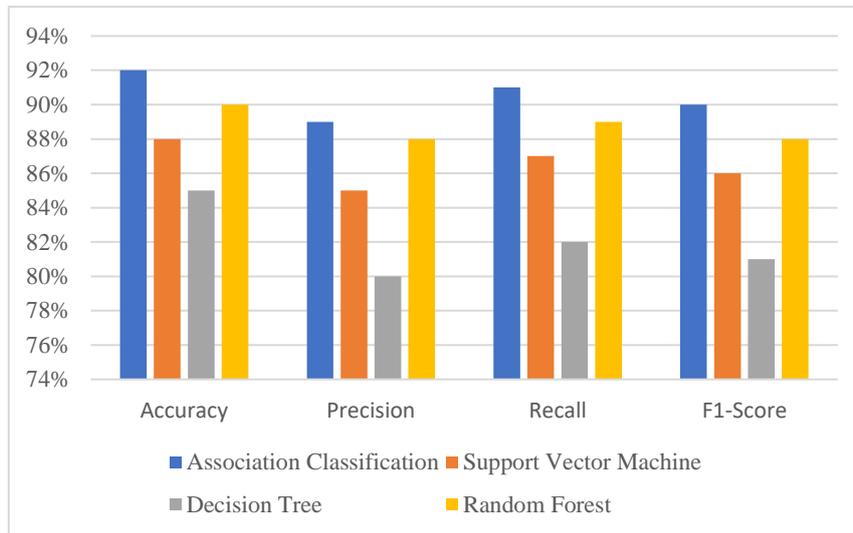


Figure 4: Comparative Performance Metrics of Association Classification and Other Classification Techniques for Skin Cancer Detection

The association classification approach fared better than the other methods in terms of accuracy, precision, recall, and F1-score, as shown in Table 6. Interestingly, the random forest method performed worse in precision and recall even though it had a high accuracy of 90%. This suggests that although the random forest model performed well in general predictions, it was not as successful as the association classification strategy in identifying malignant instances.

6.3. Interpretability of Association Rules in Medical Diagnosis

A key advantage of using association classification in medical diagnosis is its interpretability, as the generated rules clearly represent the relationships between various features in the dataset. For example, a rule might state, "If the lesion is irregular and the patient is over 50 years old, then there is a high probability of skin cancer," which allows healthcare professionals to understand and explain the reasoning behind diagnoses, thereby enhancing transparency. This interpretability fosters trust in the model's predictions, enabling clinicians to focus on critical features like lesion color, size, and shape during examinations. Overall, the effectiveness of association classification for skin cancer detection surpasses traditional methods, offering actionable insights that enhance the diagnostic process and improve patient care through informed decision-making.

7. CONCLUSION

As a result, this study shows that association classification is a very successful approach for detecting skin cancer. The results demonstrate how important association classification is to improving diagnostic procedures since it not only produces rules that are easy to grasp and communicate with patients, but also makes accurate predictions. The method's relevance stems from its ability to enhance clinical decision-making, which might eventually result in improved patient outcomes throughout the therapy of skin cancer. With a wide range of medical specialities to choose from, association classification in healthcare data mining has enormous future potential. This will open the door to more individualised and efficient healthcare solutions.

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