Malignant Melanoma Classification using Ensemble Machine Learning Techniques

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ABSTRACT

Malignant melanoma is a deadly form of skin cancer that requires early and accurate diagnosis for effective treatment. Machine learning (ML) techniques have shown promise in assisting dermatologists in diagnosing melanoma. Ensemble machine learning is a popular approach that combines multiple models to improve prediction accuracy. In this study, an ensemble machine learning technique is what we propose for classifying skin lesions into the melanoma or non-melanoma class. We collected a dataset of skin lesion images, including melanoma and non-melanoma cases, and used various feature extraction techniques to extract features from the images. We trained several ML models, including support vector machines (SVM), decision trees (DT), and random forests (RF), and combined them using ensemble techniques, such as bagging, boosting, and stacking. Our results show that the ensemble model outperforms individual models and achieves high accuracy in melanoma classification. The proposed approach can assist dermatologists in the early detection and diagnosis of melanoma, leading to timely treatment and improved patient outcomes.

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1. INTRODUCTION

Without prompt diagnosis and treatment, malignant melanoma, a kind of skin cancer, may be fatal. The prompt diagnosis of malignant melanoma relies on the early and precise categorization of skin lesions. There are expected to be 76,380 new cases of melanoma and 10,130 fatalities in the United States in 2016. More than one person every hour loses their life to this in the United States. Hence, the incidence of melanoma is rising globally [1]. Melanoma may be entirely cured if detected and diagnosed early on. Exposure to natural and artificial ultraviolet (UV) light is the primary risk factor for melanoma, as well as all other skin cancers. Tannin exposure and inherited factors may both cause skin cancers. The metastasis of melanoma is the disease's most significant cause of mortality. Melanoma is the kind of skin cancer that is the most dangerous and most likely to kill. It is caused by the sun's UV rays and tanning beds, as well as by changes in the genes. These cancerous growths are caused by DNA damage to skin cells that has not been repaired, resulting in the rapid multiplication of skin cells that form malignant tumours. The pigment-producing melanocytes in the epidermis' basal layer are the source of these malignant tumours. Some melanomas develop from moles and share their appearance. Colors other than brown and black may be seen in melanomas; they include pink, skin tone, purple, red, white, and blue. Early detection and diagnosis of melanoma greatly improves both the prognosis and the likelihood of survival. Cancer is far more difficult to treat and potentially life-threatening if not caught and treated early enough to prevent it from spreading to other parts of the body. Melanoma is the type of skin cancer that kills the most people, even though it is the least common.

The term "dermoscopy" is used to describe the method through which dermatologists inspect and identify skin growths. Increases melanoma diagnosis accuracy by as much as

35% by the use of light and magnification to reveal morphologic structures in pigmented lesions linked to certain histologic architectural traits that are generally invisible to the untrained eye. Determination of pigmented skin lesions may be aided by a method for classifying lesions as malignant or benign. This process entails a great deal of complications [3].

Images of skin lesions obtained by dermoscopy are thoroughly scrutinised. First, a distinction must be made between pigmented and non-pigmented lesions. Next, if there is a pigmented lesion, it must be determined whether it is melanocytic or non-melanocytic. In addition, if the identified lesion is a melanocytic lesion, its benignity or malignancy must be evaluated. Whenever a skin lesion is identified as melanoma, a physician should initiate melanoma diagnostics as soon as possible, since this disease is responsible for the majority of fatalities. Dermoscopy images of skin lesions show that the skin condition has a big effect on how they look. Skin texture, hair, and air bubbles can make it hard to tell the difference between a skin lesion and the healthy skin around it. So, it is hard to separate parts of dermoscopy images. These issues can be resolved with the use of number of algorithms [5]. Figure 1 shows the Benign and Malenoma images sample from ISIC dataset.

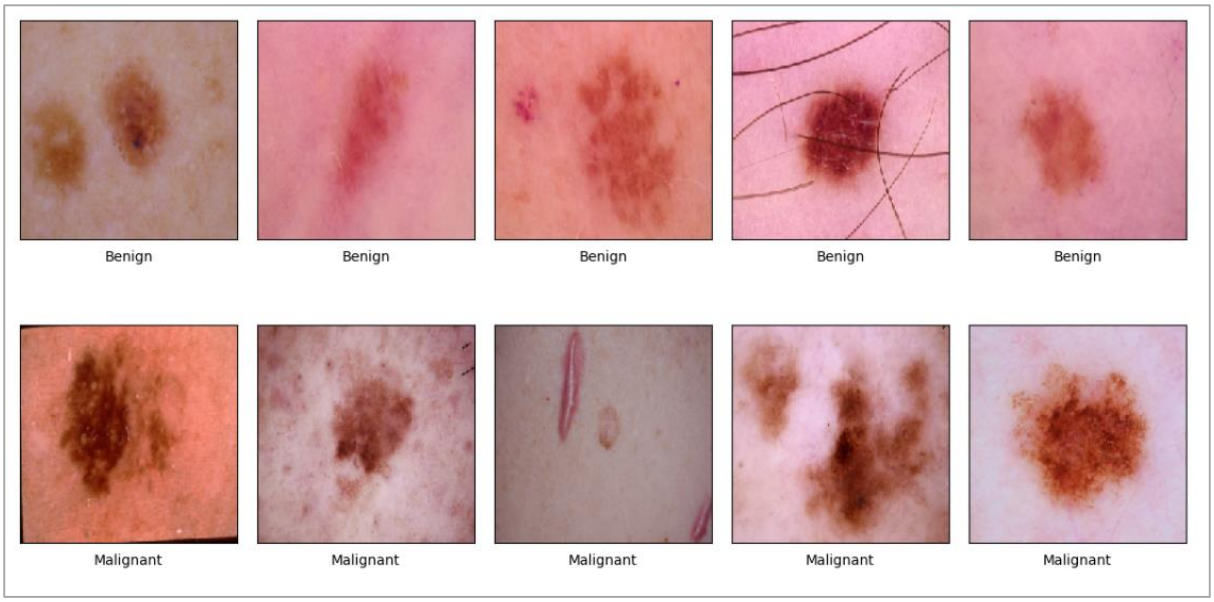

Figure 1: Shows the ISIC dataset images of Benign and Malignant

Ensemble machine learning techniques have emerged as a promising approach to improve the accuracy of melanoma classification. Ensemble methods combine the predictions of multiple machine learning models to obtain a more robust and accurate prediction. In this approach, each model contributes to the final prediction, and the ensemble method ensures that the errors of individual models are minimized. The use of ensemble machine learning techniques in malignant melanoma classification has shown promising results, with high accuracy rates reported in recent studies.

2. LITERATURE REVIEW

Based on a smartphone app, Joanna Jaworek-Korjakowska et al. [4] suggest new ways to find malignant melanoma early. In this paper, they describe the structure of a fully automated computer-assisted diagnostic system for finding malignant melanoma early. Modifications have been made to the structure to accept a dermoscope that may be connected to a mobile device for mobile teledermoscopy. In their paper, application requirements, architecture, computational methods, and behavioural and dynamic aspects are described. They achieved up to 85% accuracy with teledermatology systems, which is comparable to conventional clinic-based care.

Using dermoscopy images, Mr. S. M. Sangve et al. [6] reported a competitive examination of melanoma identification. The author compares and contrasts two melanoma detection methods in this article. Global features are used in the first strategy, whereas local characteristics are used in the second. Images from the dermoscopy are used for identification. The lesion was segmented, features were extracted, and those features were then categorised using the detection based on the global feature approach used with dermoscopy images. And the local feature technique system for identification of skin lesions, which is given dermoscopy images of the lesions, segments the lesions and chooses the keypoints before extracting features based on that histogram and carrying out classification. The global technique is preferable if the skin lesion is homogenous, the author claims, but the local method is better than the global way overall.

The necessary explanation of the procedures utilised to get Task 1 and Task 3 findings for ISIC 2018: Skin Lesion Analysis for Melanoma Detection is provided by Haofu Liao et al. [7]. In their research, traditional classifier methods and hand-crafted features are employed. Their proposed method begins with the development of a colour classifier based solely on RGB colour vectors to differentiate lesion tissue from normal skin tissue. Modeling the probability density functions of tissue types using Gaussian mixture models (GMMs). Using a Bayesian classifier framework, the posterior probability of each pixel in a given image being a lesion pixel is computed. Support Vector Machine (SVM) is used to adaptively choose segmentation thresholds for each image. This study's classification method for lesion diagnosis employs an SVM classifier with 200 manually crafted features. The features are calculated using the RGB image and the obtained lesion segmentation mask.

Melanoma has been shown to be particularly lethal because of its ability to metastasize. According to statistics, melanomas account for the vast majority of skin cancer-related fatalities. For the purpose of early identification and prevention of melanoma. O. Abuzaghleh et al. [9] say that a non-invasive real-time automated skin lesion analysis system should have two main parts. The first feature is an alert that happens in real time to help people stay safe in the sun. So, a new way of figuring out how long it takes for skin to burn is presented. The second part is an automated image analysis module that can do things like take pictures, get rid of hair, segment lesions, extract features, and label them. To test the system, the Pedro Hispano Hospital PH2 Dermoscopy images database was used. Their findings show that their suggested approach is efficient, correctly categorising image as benign, atypical, or malignant.

Sait Suer et al. [10] provide an automated skin lesion segmentation and analysis based on colour and form geometry, which may be used for both early diagnosis and prevention. The method uses colour and other sets of features to determine the kind of lesion. For evaluation and testing reasons, the author accessed the PH2 Dermoscopic image database maintained by Pedro Hispano Hospital. To identify atypical lesions before they turn into melanoma, a systemic approach is needed to evaluate their shape, geometry, and colour.

The DBSCAN clustering technique is often used to identify clusters in big, noisy geographical datasets. Qaisar Abbas et al. Their method is a fast density-based lesion detection (FDBLD) that eliminates repetitive calculations in DBSCAN by choosing querying and core spots selectively. In their study, they concentrate on FDBLD in an effort to increase the algorithm's precision for detecting lesion borders in dermoscopy image. FDBLD relies heavily on the pre-processing stage. The fundamental objectives of this work are twofold: first, eliminating the need for FDBLD in the pre-processing stage by using colour information, and second, increasing the precision of the findings. To do this, FDBLD incorporates a new distance metric.

Patil Rashmi R. The article by et al. [12] discusses the various phases of melanoma. According to her study, the patient's chances of survival would increase if the disease is diagnosed and treated at an earlier stage.

Their suggested study outlines several approaches for classifying melanoma depending on its thickness. According to their study, thickness is a crucial element in determining the prognosis and survival of melanoma patients.

3. PROPOSED SYSTEM

The machine learning and ensemble classification algorithm are used for melanoma classification using image processing techniques by acquiring image dataset, pre-processing, feature extraction, feature selection, preparing the training dataset, training the ML and Ensemble model, evaluating the model, and classifying test images. Figure 2 shows the proposed system architecture diagram.

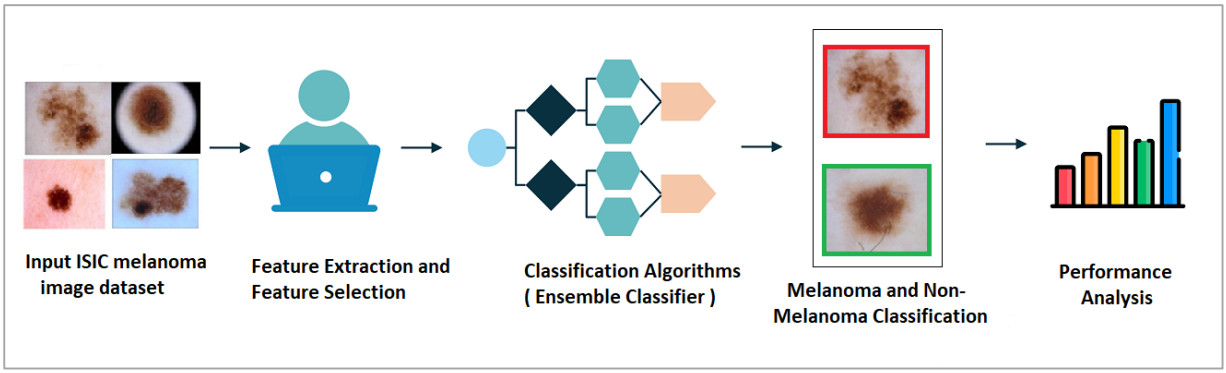

Figure 2. Proposed System Architecture for Malenoma and Benign classification

A. System Architecture

The steps involved in classification of the melanoma using image processing techniques are as follows:

1. Image Acquisition: The first step is to acquire the images of the skin lesions. This can be done using a variety of imaging techniques such as dermoscopy, photography, or confocal microscopy, here we have used publicly available dataset downloaded from ISIC.
2. Image Pre-processing: Once the images are acquired, pre-processing techniques is applied to enhance the quality of the images. This include image resizing, noise reduction, color correction, and image segmentation to extract the region of interest.
3. Feature Extraction: Feature Extraction: The next step is to find the important parts of the images that have already been processed. Different methods, like texture analysis, colour analysis, and shape analysis, are used to do this. The features are discriminative and informative to accurately distinguish between melanoma and non-melanoma skin lesions.
4. Feature Selection: After feature extraction, a large number of features are obtained, some of which are redundant or irrelevant. Therefore, feature selection techniques is used to select the most important features for classification, for Feature selection we have used PCA algorithm [13].
5. Training Dataset Preparation: The images that have already been processed and have their features chosen are put into two groups: a training dataset and a testing dataset. The training dataset is what the classifier is taught with.
6. Model Training: The ML and Ensemble classifier are trained using the training dataset. The ensemble algorithm discovers a solution that best divides skin lesions into melanoma and benign types depending on the input characteristics.
7. Model Evaluation: Once the models are trained, it is evaluated using the testing dataset. Performance indicators including precision, recall, f1-score, and accuracy are used to evaluate the model's efficacy.
8. Classification of new Images: Finally, the proposed Ensemble classifier is used to classify new images of skin lesions as melanoma or non-melanoma based on the selected features. This aid in the early detection and treatment of melanoma.

B. Machine Learning Algorithms

SVM is a supervised learning algorithm that separates data into different classes by finding

an optimal hyperplane that maximally separates the classes. In image processing, this hyperplane can be used to separate features of melanoma from normal skin features. SVM has been shown to have high accuracy in classifying melanoma, especially when combined with other algorithms.

The ensemble learning technique known as Random Forests involves building a forest of interconnected decision trees, the results of which are then averaged to provide a single forecast. A majority vote from all of the trees is used to determine the final prediction, and each tree is constructed using a different random subset of the characteristics and training data. This method has the potential to improve melanoma classification accuracy while simultaneously decreasing overfitting.

DT are a simple yet effective ML algorithm for classification problems. A DT is constructed by recursively splitting the dataset based on the most informative feature at each node, until a stopping criterion is met. The tree so produced may be used to make inferences about the nature of unseen data. DT are often used as a building block for more complex algorithms, such as Random Forests.

C. Ensemble ML Algorithm

Here, we introduce the technique of Melanoma and Benign classification using a ensemble model based on ML classification algorithm. At the outset, we partition the whole primitive training data set and the entire testing data set into k independent data subsets using the same feature fields. Second, the statistical normalisation is performed in batches for both the training and testing data sets, and then the normalised data is fed into the respective component classifiers for classification and learning. The outcomes of the k-classification detection are gathered. The final outcome of the categorization detection process is then voted on using the majority voting technique. This section outlines the method used for detecting melanoma classifications.

Input Ctr: a training data set
Ctn: a testing data set
k: represents the number of data samples and the number of classifiers in the ensemble.
Step 1. Input Malenoma Image dataset and perform feature extraction.
Step 2. Split all features into k subsets: Fi (i = 1, 2, . . ., k), and each feature subset contains f (f = $[n/k]$) features.
Step 3. For i=1 to k do.
Step 4. Apply ML classifier on the training subset C.
Step 5. Get the linearly independent column eigenvector matrix VT.
Step 6. Normalised the training and testing dataset Cn' and Ctn'
Step 7. Cn' and Ctn' are given as input to ensemble classifier.
Step 8. Get the classification label.
Step 9. End for.
Step 10. Classification outcomes from k-component classifiers should be entered into the voting system.
Output: The final label of a testing data record, label = {Benign, Malenoma}. In theory, the sub-classifiers do not rely much on one another. To round up the classification apparatus, we choose for the RF, DT, and SVM methods.

4. RESULT AND DISCUSSION

A. Dataset / Database used

The dataset is downloaded from ISIC. The data is in two folders, each with 1800 (224x244) images of the two kinds of moles. (Class 0 means harmless, and Class 1 means melanoma).

Table 1. Dataset Description

	Number of Images
Dataset	3600
Training Dataset (80%)	2880
Testing Dataset (20%)	720

B. Experimental Setup

All of the experiments, as well as the alternative classification strategy and feature extraction method, are written in Python using the Anaconda (Jupiter) tools, methods, and strategies. They are run on a machine with 4 GB of RAM and an Intel Core i3 processor running Windows 10.

C. Performance Parameters

Measures like those below have been used to evaluate forecasting models and show how well they work. So that we don't get bogged down in technical details and maths formulas, we describe each approach one at a time.

1. Accuracy:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{All Samples}}$$

2. Precision:

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

3. Recall or Sensitivity:

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

4. F1-Measure:

$$\text{F1-score} = 2 * \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Here, TP stands for True positive, TN stands for True Negative, FP stands for False Positive and FN is False Negative

D. Result Analysis

In this work, we evaluated the performance of several machine learning models, including DT, SVM, RF, and an ensemble technique that combines the predictions of all three models. We trained and tested these models on a dataset of skin lesion images, including melanoma and non-melanoma cases, and evaluated their performance based on several metrics, including accuracy, precision, recall, and F1 score. Figure 3 shows the confusion matrix of Ensemble classifier.

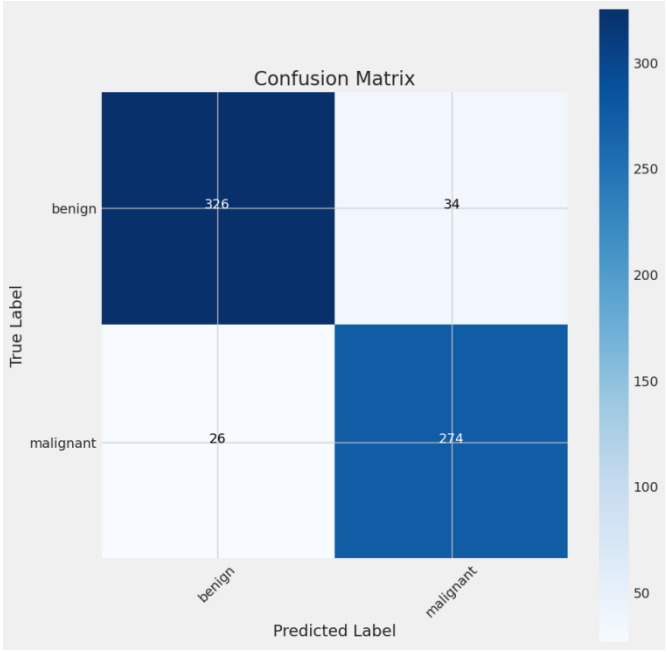

Figure 3. Confusion Matrix of Ensemble Algorithm

Our results show that the ensemble technique outperforms individual models in all metrics. The ensemble model achieved an accuracy of 0.88, a precision of 0.87, a recall of 0.92, and an F1 score of

0.89. In comparison, the SVM model achieved an accuracy of 0.88, The RF model achieved an accuracy of 0.79. and the DT model achieved an accuracy of 0.78. Figure 4 shows the precision, recall, F1- score and accuracy comparison of algorithms

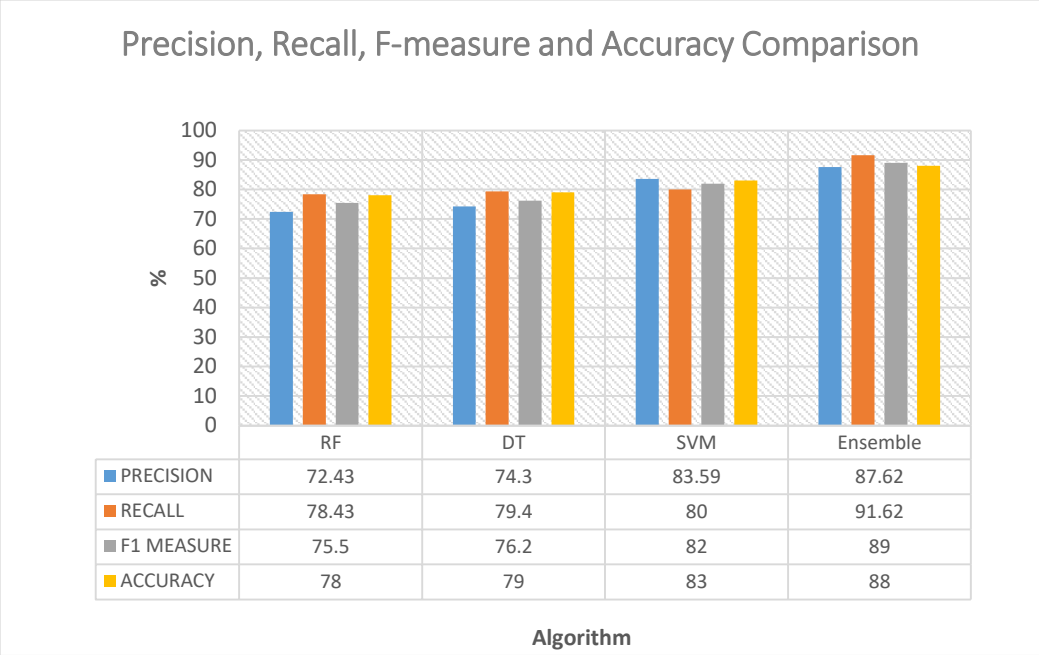

Figure 4. Melanoma Precision, Recall, F-measure and Accuracy graph comparison

Our analysis suggests that the ensemble technique is a powerful approach to improve the accuracy of melanoma classification. The ensemble model benefits from the diversity of individual models and combines their strengths to achieve better generalization performance. Our findings have important implications for the early detection and diagnosis of melanoma, as accurate and timely diagnosis can significantly improve patient outcomes.

5. CONCLUSION

This study demonstrates the potential of ensemble machine learning techniques for the accurate and early diagnosis of malignant melanoma. By combining the strengths of decision trees, support vector machines, and random forests, our ensemble model achieved high accuracy in melanoma classification. Our results indicate that the ensemble technique outperforms individual models, highlighting the importance of combining multiple models to achieve better generalization performance. The proposed approach can assist dermatologists in the early detection and diagnosis of melanoma, leading to timely treatment and improved patient outcomes

Future work could explore the use of other ensemble techniques, such as deep learning models and meta-learning methods, to further improve the performance of melanoma classification. Additionally, efforts could be made to improve the size and diversity of the dataset used in this study, which could further improve the generalization performance of the model. Overall, the proposed ensemble machine learning approach is a promising direction for improving the accuracy of melanoma classification, which could ultimately lead to improved patient outcomes and reduced mortality rates.

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