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DERMATOSCOPIC SKIN LESION CLASSIFICATION USING MACHINE LEARNING APPROACHES

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Abstract: *In this paper, we concentrate on the issue of skin lesion classification, especially early melanoma detection, and give a deep-learning based method to solve the issue of classifying a dermatoscopic image having a skin lesion as malignant or benign. We are using 10,000 MNIST HAM datasets in this process for the investigation. This paper consists of two parts. We always investigate whether a balanced dataset will deliver more accuracy than an unbalanced dataset in the first stage. Thus, to balance your dataset, we have employed a sampling technique called Synthetic Minority Oversampling Technique (SMOTE), which greatly enhances the accuracy of most device learning standards. We then investigated the accuracy of the different algorithm learning machines we used. As a final result, we conclude that the support vector machine algorithm with polynomial kernel gives better accuracy than various machine learning algorithms, such as the decision tree using Gini index and Entropy, Naïve Bayes, XGBoost, Random Forest, Support Vector Machine and Logistic Regression. We have chosen F1-Score as the diagnostic matrix, followed by accuracy, memory, and accuracy. On our device, like most, we achieved 96.825% accuracy with the support vector machine using Polynomial Kernel. We conclude that SVM with a Polynomial kernel offers more accuracy than other algorithms.*

Keywords: *Machine learning, skin Lesion classification, melanoma detection, support vector machine, Synthetic Minority Oversampling Technique.*

I. INTRODUCTION

Melanoma is a malignant form of mostly skin cancer that is often undiagnosed or misdiagnosed as a benign skin lesion. An estimated 76 cases of melanoma and 6,750 deaths each year are predicted in the United States [1]. Early detection is important: The lives of cancer patients depend on accurate and early screening. Physicians often rely on personal experience, evaluate each patient's injuries on a case-by-case basis, and consider the patient's local injury patterns over the whole body [2]. Without computer-assisted assistance, the accuracy of

ISSN: 2366-1313

scientific research in detecting melanoma is estimated to be between 65% and 80%. The use of dermatoscopic photos improves the diagnostic accuracy of skin lesions by up to 39%. However, the visible changes between cancer and benign skin lesions can be very widespread (Figure 1), making it difficult to distinguish between the two cases, even for trained health care workers. For the reasons mentioned above, an intelligent skin lesion analysis machine based on a scientific picture can be welcome tools that can help a physician classify skin lesions. In this work, we are interested in a specific problem of classification of two classes: determining whether the dermatoscopic image of the skin lesion contains melanoma or benign lesions.

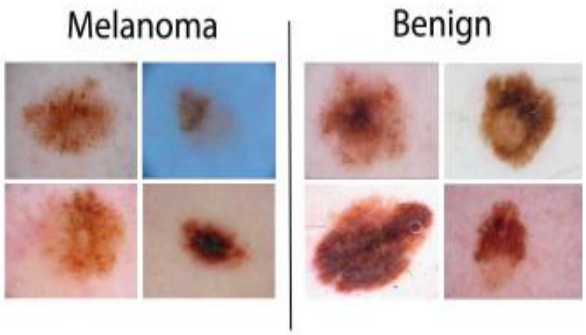

Fig.1 Sample images created from the MNIST HAM datasets

The category of malignant skin lesions plays an important role in treatment. As is known, pores and skin lesions are distinguished from the original area of \u200b\u200bthe skin. Some pores and skin lesions are harmless, while others can be very harmful. Since skin lesions are a difficult endeavor, categorizing the morphology of skin lesions can be a daunting challenge. The challenge will be much more difficult because of the environment, the noise, the hair, and the person's shadow. The beauty of the skin and pure lessons consist of several steps that begin with photography and end with teaching. In this newsletter, we have extracted tens of thousands of statistical units from the MNIST HAM reference data set, such as B. 10.5 images related to the unique pathology of follicles and skin lesions. There are 7 types of pores and skin lesions in this data set. Several machine learning and deep study algorithms are used for this type. As we generate snapshots as pixels within a CSV (comma separated values) document, we complete a benchmark using hardware distinct learning algorithms. Various algorithms were used for machine understanding, including multi-state study strategies, near-neighborhood algorithms, selection trees, logistic regression, lead vector machines, and artificial neural networks. The cancer diagnosis was completed using knowledge-enhancement techniques, with the authors making transcripts using the integrated VGG-16 network. We used algorithms including Support Vector Machine, Naive Bayes, Random Forest,

ISSN: 2366-1313

Decision Tree, Guinea Index, Entropy Use, Logistic Regression, and XGB Boost.

II. RELATED WORK

At this point, we provide an accurate description of the latest work in the field, as well as the data sets and challenges involved. The most advanced cancer class strategies are based on literal features, lesion size (primary morphology), wound correlation (secondary morphology), staining, distribution, shape, texture, and segmental irregularity. After the feature is launched, machine learning technologies such as K-Close Friend (kNN), Artificial Neural Networks (ANN), Logistic Regression, Decision Wood, and Assistive Vector Machines (SVM) will be added to the class journey with moderate performance. Examples of related paintings include the use of home posts and famous ratings.

Kudila et al.

Barata et al. [5] the dermotoscopic snapshot uses two different methods to detect cancer, primarily based on global and local capabilities. The global procedure involves the use of segmentation. It violates, Laplacean pyramids, or linear filters, which are then graded histograms to extract capabilities, including texture, shape, and color, from the entire wound. After that, the binary classifier is trained with statistics. The second neighborhood capability technique uses a bag of features (BoF) classification for photo processing tasks (i.e. object identification). They concluded that color abilities work much better than self-made abilities.

These days, the rise of the so-called insight system study model has enabled the development of medical image diagnostic systems that can show surprising accuracy, even raising questions about the future of the human radiologist. Convolutional neural networks have had promising effects on the classification of skin lesions.

Samples of related work that cover the use of deep learning include.

The work of Kawahara et al. [6] explores using pre-trained ConvNet as a function extractor instead of training CNN from scratch. Furthermore, it demonstrates pre-trained CNN filters on herbal images, which are common for classifying 10 classes of non-dermoscopic images of the skin.

Liao's et al. [7] The papers attempted to construct an established type of skin disease using deep CNN transfer mastering and adjusted their first-degree weight by continuing back-propagation.

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Codella et al. [8] The authors document new state-of-the-art performance using ConvNets to extract image descriptors using a pre-trained version of the Image Mass Visual Recognition Challenge (ILSVRC) 2012 dataset. They also check out the latest forms from the community to win the popular ImageNet job called Deep Residual Network (DRN)

In [9], the classification of atopic dermatitis as a multiclass disorder may depend on the rate obtained from the severity score calculated using the SVM multiclass classification. SVM classification is taught with the help of 22 abilities derived from three main features colour, texture and caption. No single data set was used for diagnostic purposes. The educational set was taken from a total of 100 photographs of 55 patients, and the test set was taken from two patients. And based on the intensity score, it is likely to be classified as None, Light, Light and Extreme. As a result, they achieved a general accuracy of 86% with 10 times pass validation.

III. PROPOSED WORK

In this paper, we are going to specialize in pre-processing and classification. We found many of the related paintings were used in unbalanced datasets, so accuracy is not always accurate. Most of them did not take a balanced set of facts, and they used only a limited number of images or substandard datasets. We have taken the usual HAM10015 dataset, which includes 10015 images of skin lesions with 7 classes. The draft diagram of the proposed work is shown in Figure 2.

A. Preprocessing

The proposed method uses an up-sampling technique called Artificial Minority Oversampling Technique (SMOTE) to balance the dataset. After testing the use of SMOTE, there are 6705 samples of each type of skin wound.

B. Classification

After weighing the facts, the next step is to teach the samples how to use models automatically and classify the data sets. In this article, we have categorized the dataset based on the maximum use of the tool to gain insights into the algorithm and compare the rule set for better accuracy. The algorithms we used here are Naive Bayes, Logistic Regression, Decision Tree Classifier, Gini Index, Use Entropy, Support Vector System, Use All Viable Grain Types, and XGBoost. We have implemented the set of rules with default parameters, and the proposed set of paint rules is shown below.

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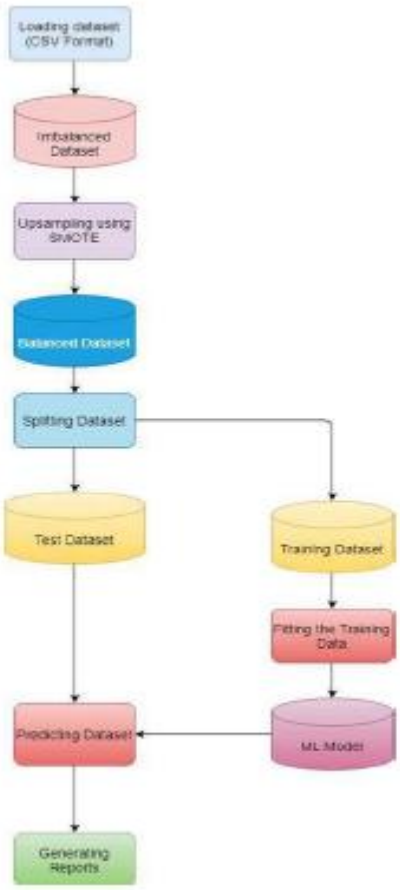

Fig.2 Flow Diagram of the proposed work

XGboost Algorithm

Step1: Loading the Dataset

Step2: Balancing the dataset using SMOTE

Step 3: Split the dataset into training and test data

Step 4: Develop Machine Learning Models (SVM)

Step 5:Evaluate the models using Testing Da

IV. RESULTS AND DISCUSSIONS

The proposed method is built with Windows 64, 8GB RAM with Anaconda for Python 3. Several tools for learning algorithms for processing datasets and 8 for implementing pandas library. The MNIST HAM1000 register is used to implement the proposed device, which can be accessed via an ISIC entry. The dataset contains 10015 pixels in seven guidelines. Of the 10015 completed facts, the dataset included 6,705 samples of birthmark lesions, 114 dermatofibromas, 1114 samples of malignant follicles and skin tumors, and 1099 benign keratosis symptoms, 514 samples and signs of actinic keratosis in 327 samples and samples. Because the data set is very different from what normal and minority people suggest, it is an unbalanced data set. Figure 2 shows a variety of wound patterns for each skin type. In our machines, the dataset is in the form of a CSV (Comma Separated Values) file, where the dataset contains the pixel values of the images in the dataset. So our CSV report is no longer made up of features but has an honest image pixel format (~2351 pixels per image).

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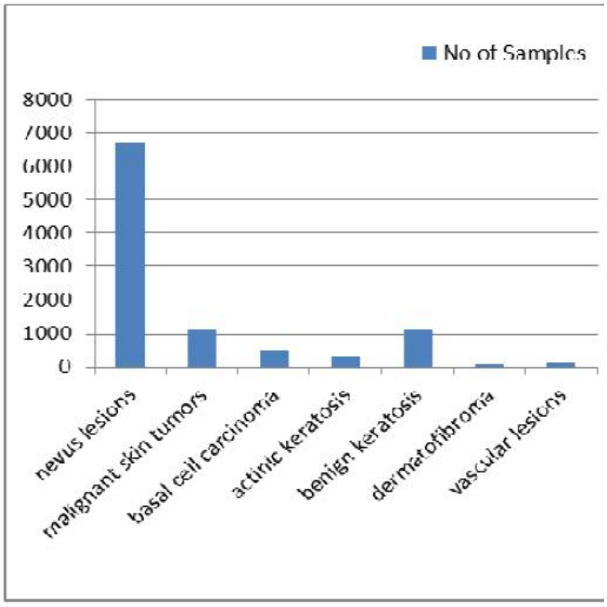

Fig.3 Number of samples in each type of skin lesions in HAM10000 dataset

V. PERFORMANCE EVALUATION

To evaluate the model, we have taken Accuracy as the most important evaluation metric. The Accuracy got by different machine learning models in balanced and imbalanced datasets was given in the Table.1

Table.1 Accuracy Results for various machine learning algorithms

Machine Learning Algorithms	Imbalanced (%)	Balanced (%)
Logistic Regression	67.354	82.451
Naïve Bayes	44.392	39.571
Random Forest	72.013	95.227
Decision tree (Entropy)	63.904	85.447
Decision Tree (Gini)	61.457	83.896
SVM (kernel=Linear)	61.008	95.067
SVM (Kernal=Poly)	**69.695**	**96.825**
SVM (Kernal=rbf)	70.843	92.372
XGBoost	70.43	95.984

We also considered the f1 value, the value, the accuracy, the sensitivity, and the specificity to evaluate the machine recognition method. The results of the above evaluation metrics are presented in Table 2.

Accuracy: Accuracy is the ratio of the total number of instances of the correct prediction. Accuracy calculated as follows

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

Sensitivity: Sensitivity is used to determine the portion of the actual positive instances case classified adequately by the classifier. Sensitivity calculated as follows

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

Specificity: Specificity is used to know the ability of classifiers to identify incorrectly classified negative cases

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

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Precision: Precision is an indicator that defines the true portion of the instances when predicted to be true. Precision calculated as follows-

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

F1 Score: F1 Score is a harmonic mean of recall and precision. It must be one for good performance and zero for the bad performance of the classification algorithm. F1 score calculated as follows

Table.2 Evaluation results for various machine learning algorithms

Machine Learning Algorithm	Precision (%)	Recall (%)	F1-Score (%)	Sensitivity (%)	Specificity (%)
Logistic Regression	82	83	82	83.74	7.19
Naïve Bayes	42	40	40	41.97	88.21
Random Forest	95	95	95	95.82	99.17
Decision Tree (Entropy)	85	86	85	86.03	97.58
Decision Tree (Gini)	85	85	85	85.87	97.59
SVM (Linear)	95	95	95	95.80	99.15
SVM (Polynomial)	**97**	**97**	**97**	**97.29**	**99.45**
SVM (RBF)	92	92	92	92.79	98.73

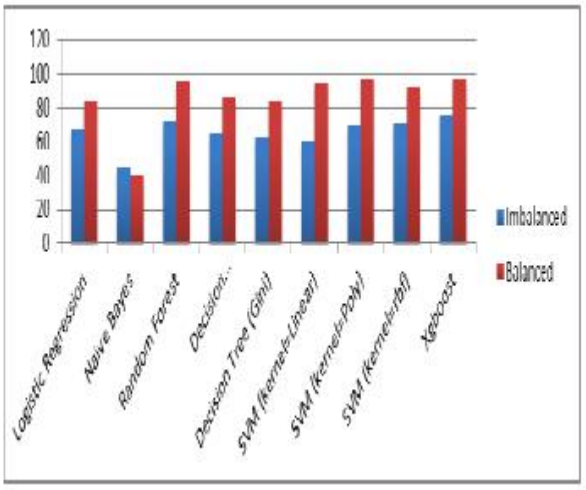

Fig.4 Final comparison between various machines learning algorithm's in Lesion Classification

VI. CONCLUSION

We have seen that balancing the data set significantly increases the accuracy of the results by observing the results. In our work, the data set was modeled using the SMOTE model. In conclusion, we conclude that a supporting vector machine with a polynomial kernel provides better accuracy than other machine learning algorithms. Our current observation focuses only on the preprocessing and classification of endoscopic images. In the future, we intend to focus on methods for separation and feature extraction from dermatoscopy images using models that have a deeper understanding of using images as input records.

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ISSN: 2366-1313

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