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Evaluating Machine Learning Models for Multi-Label Skin Cancer Classifications and Detection

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Abstract—

A lack of knowledge about the symptoms and ways to avoid skin cancer makes it one of the most prevalent and deadly illnesses. The alarmingly high mortality toll from skin cancer makes this illness a potential "fourth burden" on the global health system. Consequently, in order to halt the progression of cancer, early diagnosis is crucial. Using methods from machine learning and image processing, we identify and categorize multi-label skin cancer in this research and put the best practices into practice. On the other hand, pretreatment techniques help get rid of superfluous features from the label encoder, and standard features are used to scale the input variance unit and standardize the range of functionality. In addition, the HAM10000 metadata dataset was used to evaluate each classifier's performance using a variety of machine learning approaches. Seven distinct skin cancer types were included in the HAM10000 metadata dataset, which was used for the experimental study. According to the findings, SVM, DT, and GNB, which are machine learning algorithms, outperformed the other classifiers in terms of accuracy. Skin cancer, ML, classification, support vector machine, decision tree, gross national bias, multi-class The National University of Iqra Shah Hussain Bangash in Peshawar, Pakistan the email address is shahhussain@inu.edu.pk. National University of Peshawar, Pakistan, Atif Ishtiaq Iqra Your email address is atif.ishtiaq@inu.edu.pk. Although it may not be well known, skin cancer affects a significant number of individuals globally. The sun's harmful ultraviolet (UV) rays cause skin cancer. Sunlight, in the form of ultraviolet (UV) rays, reaches Earth after passing through our atmosphere. It comes in several forms and may manifest on any part of the skin. There are methods to lessen the likelihood of unstable skin cancer cells effeteness, albeit it is not always prevented. Cancer of the skin is a major health concern that poses a significant risk [4]. It's important to be aware of the risks and to take measures to protect yourself against cancer waves. Quite a few people in the US suffer from this illness [5]. While melanoma accounted for over 63,000 new cases in 2012—making it the most deadly kind of skin cancer—more than 6 million new instances of non-melanoma skin cancers (NMSC) were discovered same year, according to the skin cancer foundation. When skin cells start to proliferate uncontrollably, we get skin cancer. Melanoma develops when skin cells proliferate deeper in the dermis, while non-melanoma skin cancer (NMSC) occurs when this occurs at the lower layers of the epidermis [6].

INTRODUCTION

Skin cancer is a prevalent and widespread illness that affects many nations. It may develop in people, animals, and plants, but it has a distinctive feature that makes it stand out. The alarming rise in skin cancer cases is putting a heavy strain on healthcare systems throughout the globe. Worldwide, skin cancer ranks as the fourth leading cause of mortality. Its primary victims are the young and the old, yet it may impact anybody at any time [1]. Early detection of the condition allows for a surgical procedure to treat it. Melanoma, basal, and squamous cell varieties are all present [2]. Among cancers, melanoma is the most unexpected. Hair follicles, skin cells, and

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mucous membranes are all affected. Cancer of the skin may develop in almost every damaged skin cell. When skin cells undergo a mutation and become cancerous, it may impact almost everyone. Any area of your body is fair game for carcinomas, the medical term for skin malignancies. According to studies, skin cancer may be caused by prolonged exposure to high quantities of solar radiation, namely ultraviolet (UV) rays [3].

RELATED WORK

Automated skin cancer categorization with several classes and levels has been the focus of machine learning efforts for the last 20 years. Skin cancer, handicap, and global distress may be better tackled with the use of machine learning and deep learning, according to Nazia Hameed et.al. Algorithms for categorization have shown promise in improving the treatment of a variety of skin lesions [7]. In order to control the average feature extraction from anecdotal pictures, A. Murugan et.al. examined the implications of skin color purification and segmentation in human disorders. When compared to other methods, the combined outputs of SVM and RF show superior accuracy [8]. Possible infrared thermography observation approaches that use machine learning methods to skin cancer were suggested by Carolina Magalhaes et.al. In order to reduce the confusion matrix and improve prediction performance, ensemble learning based on input thermal characteristics was used in the investigation of skin cancer diagnoses [9]. According to Mehwish Dildar et al., melanoma develops because human skin cells constantly transmit damaged deoxyribonucleic acid. Early cancer identification is key for controlling symptoms, ensuring significant medical care, and taking other factors such as color, form, symmetry, etc. into account. Researchers have tried a number of different machine learning and deep learning approaches to skin cancer detection in the past, but their results have been lacking [10]. In an effort to shed light on the human condition, Yuheng Wang et al. examined cancer detection tools that use polarization deep learning to illustrate images of the disease and analyze statistical patterns. Classifying skin lesions as either malignant or benign is a challenge when using deep learning and machine learning techniques [11]. Melanoma, according to Rashmi Patil et.al., is the most dangerous kind of skin cancer, and diagnosing it using machine learning techniques for categorization might be a real pain for patients. To solve the loss function and text processing melanoma tumor thickness classification issue, the suggested method used a CNN model [12]. According to Ravi Manne et.al., dermatologists may benefit from the data's higher accuracy thanks to deep learning techniques that use convolution neural networks to make skin cancer segregation easier. Reducing misclassification of pictures and improving accuracy via weaknesses in deep learning approaches was achieved by the CNN model that was examined [13].

METHODOLOGY

Efficient multi-label data classification utilizing SVM, DT, KNN, GNB, Logistic Regression, and SGD Classifier is the goal of the proposed method. Prior to any analysis, data must be prepared for categorization, and then performance will be assessed. The suggested system architecture is shown in Figure 1.

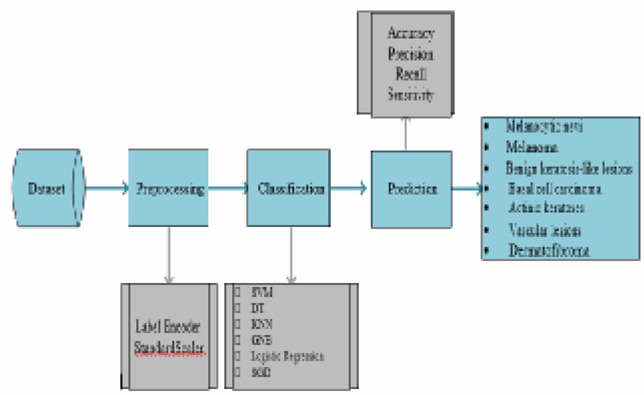

Fig 1: Proposed methodology to Skin cancer classification

data. In addition, the input data range and set were institutionalized by scaling to unit variance using a typical scalar component [13]. B. Classification: For data with multiple labels, we used a variety of classification methods, including SGD Classifier, Logistic Regression, KNN, GNB, and DT. Multiple label categorization SVM Semantic Vegetation Matching (SVM) is a reusable supervised technique for regression and classification issues. In order to solve issues involving binary classification, the SVM applies the same technique. Subproblems are created to address the multi-classification issue. When doing

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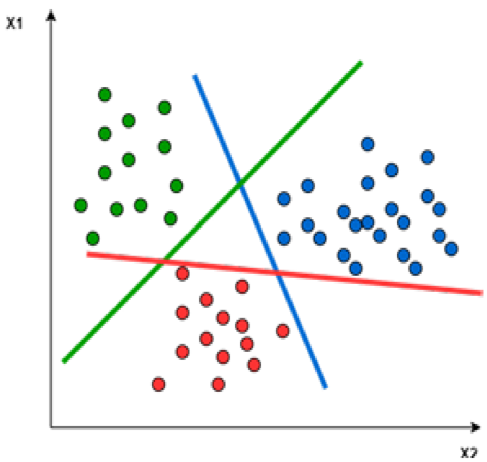
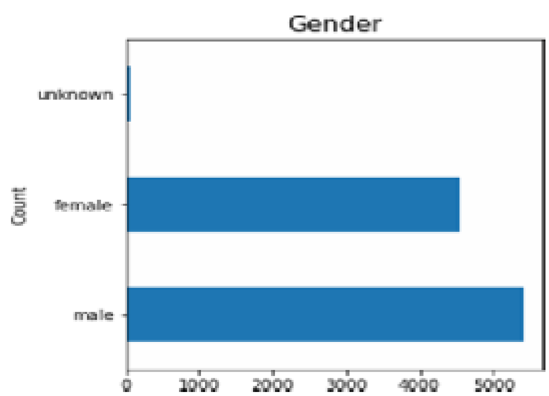
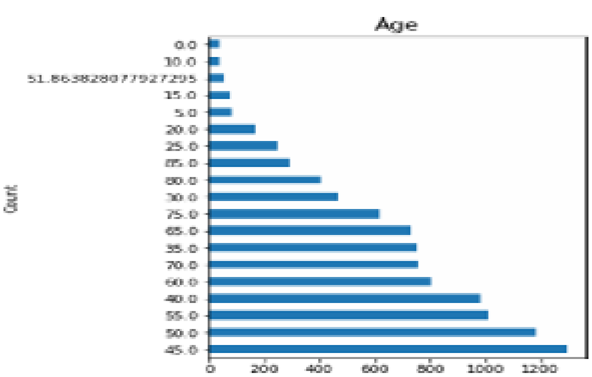
multi-classification on the issue statement, the One vs. All (OVA) technique is a prominent way. In the One vs. All method, the classes are divided along the hyperplane into two groups: one for each class point and another for all other points. The green line maximizes the distance between the green point and all the other locations, as shown in Figure 2 [14].



Classification with multiple labels DT When it comes to multi-label classification, the DT classifier is the way to go. The questions are presented in a tree structure and are based on traits and qualities. Data is partitioned into distinct records according to various attributes at each internal node in the root. The data is divided into distinct groups by the leaves on the tree [15]. Multiple label categorization KNN Classification using KNN, a supervised machine learning approach, is possible. The data structure is not a determinant of the KNN algorithm's performance. By using the formula for the geometric mean, we can get the distance between the two feature vectors [16]. Multiple label categorization GNB Bye's theorem is the basis of NB, a probabilistic ML approach used for classification. For training data, several functions are used to determine whether the data transit follows a normal or gaussian distribution. To use GNB, we must first determine the variance and mean of X and then replace in the normal distribution's probability thickness [17]. Multiple label categorization Rational Regression LR is a classification method that uses supervised machine learning. By redefining the loss functions and shifting the distribution of the predicted probabilities to a multinomial form, one-vs-rest enables the LR method to be used to situations involving many classes of data [18]. Multiple label categorization SGD Detector Using SGD as a foundation, linear classifiers and regressors with convex loss functions, such (linear) Support Vector Machines and Logistic Regression, may be quickly and efficiently trained. Despite SGD's lengthy tenure on the machine learning association, it is only very recently that it has garnered substantial interest within the framework of large-scale learning [19]. Chapter C. Dataset For the sake of this article, we repurposed the HAM10000 metadata data set from the Kaggle repository. Data is gathered from diverse groups and stored using various methods. Researchers may observe on massive data solving ML jobs using dataset, an open-source machine learning database. Two types of data were included in the dataset: training and testing. The machine learning models were trained to monitor the properties of the dataset and make predictions about them in real-time [20]. Figure 3 displays the distribution of data for several variables, including gender, age, cell type, and location. Based on the data's behavior, it's clear that improper data grouping would provide inefficient results when applying ML approaches to the data. Only 20% of the dataset was used for testing, while 80% was repurposed for training.





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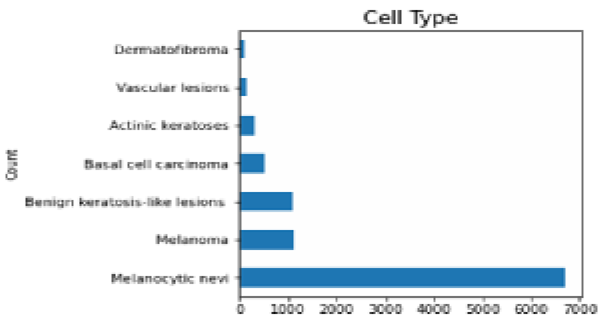

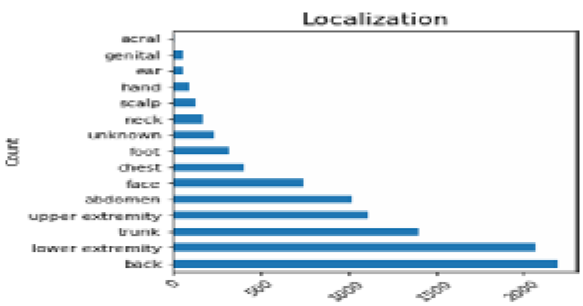

Fig 3: Distribution of different attributes values from the dataset

RESULT AND DISCUSSION

Here you may find a variety of categorization models along with an analysis of each. The HAM10000 metadata dataset was used to evaluate the effectiveness of each classifier using six distinct machine learning techniques: SVM, DT, KNN, GNB, Logistic Regression, and SGD. Prior to classifiers, the data undergoes normalization and standardization. In this experiment, several machine learning classifiers are trained and evaluated using the data. Training made use of 80% of the data, whereas testing made use of 20%. From Table 1 to Table 6, you can see the outcomes of several machine learning methods. What follows is a more in-depth explanation of label mapping: 0: Varicella melanocytic (NV) First, melanoma 2: BKLs, or Benign Keratoses Thick-Skinned Cancer (BCC) 4: AKIEC, or Intraepithelial Carcinoma 5. Valve Artery Stenosis (VASC) 6. DF has been identified. Table 1: Classification using multiple labels SVM

	precision	recall	f1-score	support
0	1.00	1.00	1.00	61
1	1.00	1.00	1.00	96
2	1.00	1.00	1.00	228
3	1.00	1.00	1.00	37
4	1.00	1.00	1.00	1327
5	1.00	1.00	1.00	222
6	1.00	1.00	1.00	32
accuracy			1.00	2003
macro avg	1.00	1.00	1.00	2003
eighted avg	1.00	1.00	1.00	2003

Table 2: Multi labels classification DT

	precision	recall	f1-score	support
0	1.00	1.00	1.00	61
1	1.00	1.00	1.00	96
2	1.00	1.00	1.00	228
3	1.00	1.00	1.00	37
4	1.00	1.00	1.00	1327
5	1.00	1.00	1.00	222
6	1.00	1.00	1.00	32
accuracy			1.00	2003
macro avg	1.00	1.00	1.00	2003
weighted avg	1.00	1.00	1.00	2003

Table 3: Multi labels classification KNN

	precision	recall	f1-score	support
0	0.85	0.82	0.83	61
1	0.86	0.85	0.86	96
2	0.91	0.99	0.95	228
3	0.94	0.43	0.59	37
4	0.96	0.99	0.98	1327
5	0.95	0.89	0.92	222
6	1.00	0.06	0.12	32
accuracy			0.95	2003
macro avg	0.92	0.72	0.75	2003
weighted avg	0.95	0.95	0.94	2003

Table 4: Multi labels classification GNB

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	precision	recall	f1-score	support
0	1.00	1.00	1.00	61
1	1.00	1.00	1.00	96
2	1.00	1.00	1.00	228
3	1.00	1.00	1.00	37
4	1.00	1.00	1.00	1327
5	1.00	1.00	1.00	222
6	1.00	1.00	1.00	32
accuracy			1.00	2003
macro avg	1.00	1.00	1.00	2003
weighted avg	1.00	1.00	1.00	2003

Table 5: Multi labels classification Logistic Regression

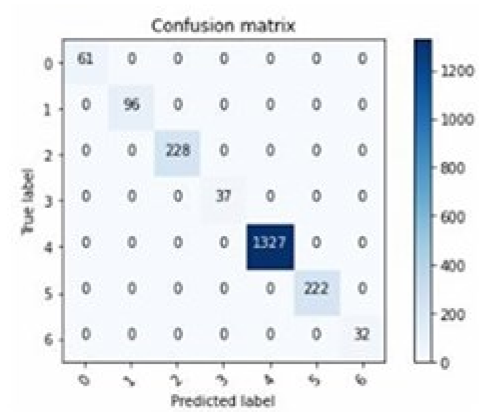
	precision	recall	f1-score	support
0	1.00	1.00	1.00	61
1	1.00	1.00	1.00	96
2	0.97	1.00	0.98	228
3	1.00	0.38	0.55	37
4	1.00	1.00	1.00	1327
5	0.93	1.00	0.97	222
6	1.00	1.00	1.00	32
accuracy			0.99	2003
macro avg	0.99	0.91	0.93	2003
weighted avg	0.99	0.99	0.99	2003

Table 6: Multi labels classification SGD Classifier

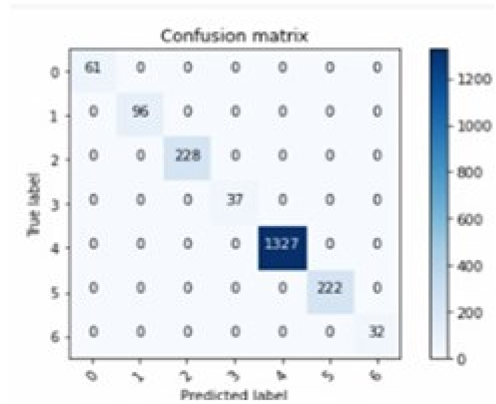
	precision	recall	f1-score	support
0	1.00	1.00	1.00	61
1	0.00	0.00	0.00	96
2	0.69	0.36	0.47	228
3	0.00	0.00	0.00	37
4	0.93	0.98	0.96	1327
5	0.43	0.74	0.54	222
6	0.00	0.00	0.00	32
accuracy			0.80	2003
macro avg	0.44	0.44	0.42	2003
weighted avg	0.77	0.80	0.78	2003

Confusion Matrix

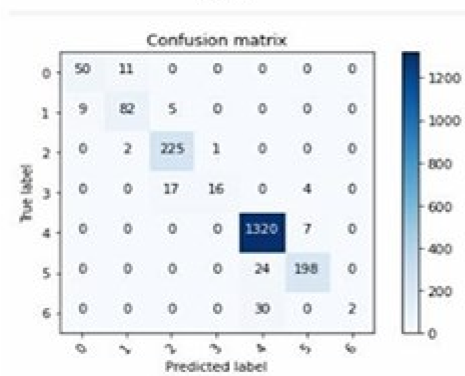
The skin cancer categorization confusion matrix, showing seven distinct classes and their respective prediction results, is shown in Figure 4. A confusion matrix is a useful tool for visualizing the results of machine learning algorithms. Moreover, the majority of datasets include data that is imbalanced and have a greater number of instances of data that is unrelated to the original class. By using confusion matrix techniques, the model can accurately predict all characteristics, resulting in the greatest possible accuracy score. The confusion matrix reveals that during testing and training, the SVM, DT, and GNB performed better than the control group on all four metrics: accuracy, precision, recall, and F1-score.



DT



KNN



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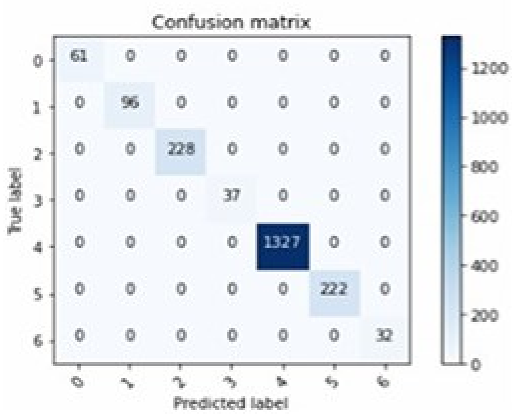
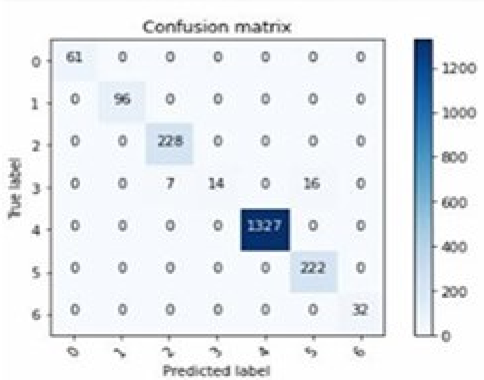
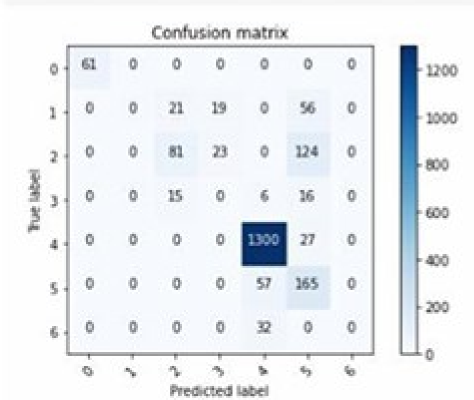
GNB



Logistic Regression



SGD Classifier

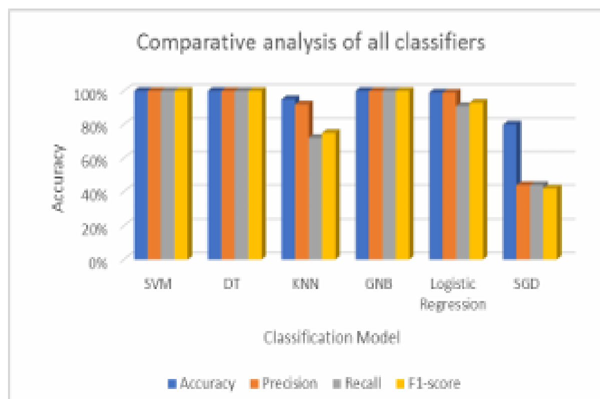


The confusion matrix of several classifiers (SGD, SVM, DT, KNN, GNB, and Logistic Regression) is shown in Figure 4. B. Total Effectiveness According to Table 7 and Figure 5, the SVM, DT, and GNB classifiers achieved the maximum accuracy when compared to all other classifiers.

Table 7: Comparison of all ML classifier

Machine Learning Classifier	Mean of Machine Learning Classifiers				
	Acc	Prec	Rec	F1-sco	Support
SVM	100%	100%	100%	100%	2003
DT	100%	100%	100%	100%	2003
KNN	95%	92%	72%	75%	2003
GNB	100%	100%	100%	100%	2003
LR	99%	99%	91%	93%	2003
SGD	80%	44%	44%	42%	2003

With perfect accuracy, precision, recall, and F1 Score, the SVM, DT, and GNB work well. With a recall of 91% and an F1-score of 93%, the logistic regression has attained an accuracy of 99%. A 75% F1-score, 92% recall, 92% precision, and 95% accuracy were all attained by the KNN classifier. A minimum performance accuracy of 80%, with 44% precision, 44% recall, and 42% F1-score, has been attained using the SGD classifier. Support vector machines, decision trees, and gaussian naive bayes classifiers outperformed all of the other machine learning algorithms in terms of accuracy, as seen in Table 7 and Figure 5.



CONCLUSION

The annual occurrence of skin cancer is alarming and pervasive. Worldwide, 5.4 million new melanoma cases are recorded annually, with 53.3% of those instances receiving a diagnosis. We evaluated seven different label datasets in this work by applying various machine learning methods on the skin cancer

HAM10000 metadata dataset. Out of all the classifiers tested, SVM, DT, and GNB performed at the highest level of performance (100% accuracy). In comparison, KNN achieved 95% accuracy, Logistic regression 99% accuracy, and SGD earned 80% accuracy. We want to evaluate this dataset's performance using more categorization methods in the future.

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