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(Research Article)

Logistic Regression for Multiclass Classification of Dermatology Disorders: A Comparison of One-vs-One and One-vs-Rest Approaches

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Abstract

This research investigates the application of Logistic Regression for multiclass classification in dermatology, focusing on the task of identifying and categorizing six distinct dermatological disorders. The study compares two widely used multiclass classification strategies—One-vs-One (OvO) and One-vs-Rest (OvR)—to evaluate their performance in the context of dermatological disorder classification. The dataset used in this study consists of feature-rich data corresponding to various skin diseases, making the classification problem both complex and challenging. Logistic Regression, known for its simplicity and interpretability, is applied to both strategies, and the outcomes are assessed based on key metrics including classification accuracy, precision, recall, and F1-score.

Through a detailed comparative analysis, the paper highlights the advantages and limitations of each approach in terms of classification effectiveness, computational efficiency, and robustness against class imbalance. The results demonstrate that both OvO and OvR strategies provide high accuracy and reliable classification performance, although differences in their predictive strengths are observed for specific dermatological conditions. The study concludes that Logistic Regression, when paired with either strategy, holds substantial promise for enhancing automated dermatological diagnosis and could serve as a valuable tool for clinicians in real-world applications. Furthermore, the findings offer insight into the optimal selection of classification approaches for various machine learning tasks within the healthcare domain.

Keywords: Logistic Regression (LR), Multiclass classification techniques, One-Versus-One(OVO), and One-Versus-Rest (OVR) strategies, Python, Support Vector Machine (SVM).

1. Introduction

Skin problems are a serious overall health issue that affects a large number of people. As of late, with the quick headway of innovation and the utilization of various information mining draws near, treatment of skin prescient arrangement has truly become exceptionally prescient as well as exact. The main component of the human body is the skin. The skin saves the body from UV beams, diseases, wounds, temperature, and harmful radiation, as well as supporting vitamin D3 [2]. Since the skin is so fundamental in overseeing body temperature and shielding the body from skin problems, it's essential to keep it healthy. Skin issues might seem innocuous, yet they can be risky on the off chance that not treated as expected. Numerous illnesses have early side effects; however, the majority of them are indistinguishable, making it hard to diagnose the condition at an early stage. Skin problems cause physical as well as mental issues, especially in people whose appearances have been scarred or distorted. Skin can be impacted by a range of external and internal factors. Counterfeit skin injury, extreme substance causes, difficulty sicknesses, an individual's vulnerability, and hereditary oddities are a portion of the factors that impact skin issues. Skin illnesses can significantly impact individuals' lives, affecting their physical health, emotional well-being, and quality of life [3][5][13]. Dermatological ailments are the most difficult subfields of science to fix due to the confusion in treating side effects and how side effects are modified in different circumstances [8]. Skin diseases are regular among numerous ailments, and on the off chance that these strategies are not good for that type of skin condition, it will cause adverse consequences. Individuals are habitually contaminated by skin diseases, which should be treated straightaway. Thus, the kind of AI approaches prepared to effectively separate skin condition arrangements is fundamental. To date, no single AI approach has consistently

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outperformed others in the prediction or diagnosis of skin diseases.

2. Methodology

2.1 Data preparation: Before experimentation, we performed data preprocessing, including data cleaning, feature selection, and standardization to ensure that the dataset was suitable for training and evaluation.

2.2 Model evaluation: We conducted rigorous model evaluation using suitable metrics, including accuracy, precision, and recall, to assess the effectiveness of each strategy in correctly classifying instances into the six distinct classes.

3. Algorithm Implementation

We implemented the Logistic Regression algorithm with both the One vs One and One vs Rest strategies [6]. These strategies were chosen to evaluate their performance in handling the multiclass classification problem.

3.1 Multi-characterization strategic relapse[10]: In the context of dermatological disease classification, both One-vs-One (OvO) and One-vs-All (OvA) approaches are used to handle the multi-class nature of the problem. The Dermatology dataset contains multiple disease classes, and standard classifiers like SVM or Logistic Regression are inherently binary. To adapt these for multi-class classification:

3.1.1 One-up against One (O v O):

- In this methodology, a twofold strategic relapse model is prepared for each set of classes.
- For instance, assuming there are 'k' classes, the O v O strategy would make k(k-1)/2 double classifiers.
- During the forecast, every classifier is applied to the information, and the class that gets the most "votes" is chosen as the last expectation.
- O v O can deal with complex choice limits yet may require more computational assets and preparation time compared with other techniques [1][4][7].

3.1.2 One-versus Rest (OvR):

- In this methodology, a double-calculated relapse model is prepared for each class versus the other classes.
- For 'k' classes, 'k' paired classifiers are made.
- During forecast, every classifier is applied to the information, and the class with the highest anticipated likelihood is chosen [9][10].
- OvA is less difficult and quicker compared with OvO, as it requires preparing 'k' parallel classifiers rather than 'k(k-1)/2', yet it may not deal with covering classes as effectively.

During prediction, OvA selects the class with the highest confidence score, while OvO uses a majority voting mechanism across all pairwise classifiers to determine the final class label. Both strategies allow traditional binary classifiers to be extended effectively for dermatological disease classification.

4. Experimental Results

In this study, we conducted experiments utilizing Python programming to perform multiclass classification using Logistic Regression. The experiments were carried out on the Dermatology dataset, which comprises 366 instances and includes 35 attributes [11]. Before model training, we preprocessed the data. The Dermatology dataset contains no missing values. We applied feature scaling using normalization to transform the data. The primary objective was to classify instances into one of six distinct class labels, denoted as follows (shown in Figure 1):

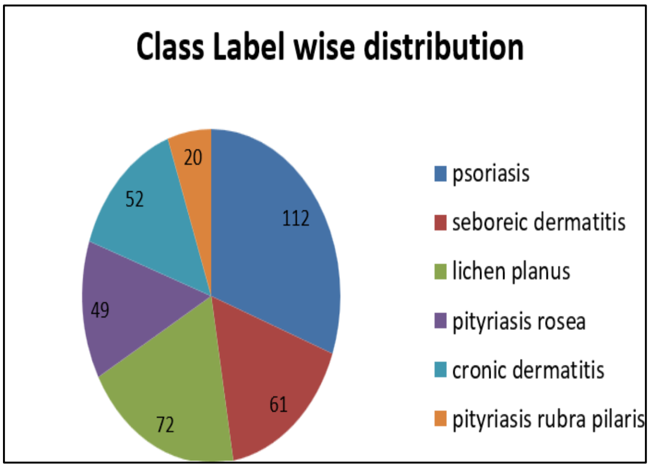

Figure 1. Class-wise labels

4.1 Results and discussion: In this study, we applied Logistic Regression to the multiclass classification of dermatological disorders, comparing the performance of two commonly used strategies: One-vs-One (OvO) and One-vs-All (OvA). The results obtained from our experiments show that both strategies achieved high classification performance, with the OvA approach marginally outperforming the OvO approach across all evaluation metrics are shown in Figure 2.

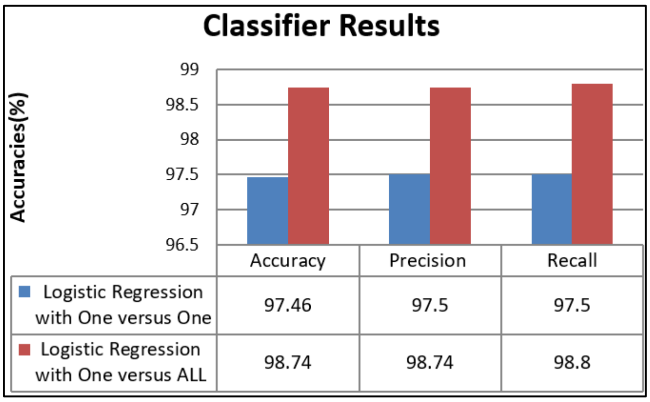

Figure 2. Experimental results

4.1.1 Performance of logistic regression with One-vs-One strategy: The Logistic Regression model with the One-vs-One (OvO) strategy achieved an accuracy of 97.46%, indicating a high level of correct classification for the six dermatological disorders in the dataset. Additionally, the precision and recall for this approach were both 97.5%, demonstrating that the model was highly effective in identifying both positive and negative instances across the classes.

The One-vs-One strategy works by training a classifier for every pair of classes, resulting in a total of n(n−1) / 2 classifiers for n courses. In the case of six classes, this results in 15 classifiers. This pairwise approach can improve performance when the classes are well-separated or when the decision boundaries between classes are distinct. However, the model may also face challenges in cases where the decision boundaries between classes overlap, as it must rely on each classifier to decide between only two classes at a time, without considering the overall multiclass structure.

4.1.2 Performance of logistic regression with One-vs-All strategy: In contrast, Logistic Regression with the One-vs-All (OvA) strategy achieved an accuracy of 98.74%, surpassing the OvO strategy by a margin of 1.28%. The precision and recall for this approach were 98.74% and 98.8%, respectively, further highlighting the superior performance of the OvA approach.

The One-vs-All strategy constructs a separate binary classifier for each class against all the others, which means that for nnn classes, nnn classifiers are trained. Each classifier focuses on distinguishing a single class from the remaining classes, allowing the model to learn the class-specific decision boundary more holistically. The OvA approach can be advantageous when the classes have more complex relationships or when there is a need to evaluate a class in the context of all other possible classes. The higher accuracy, precision, and recall rates observed with OvA in this study suggest that this strategy is better suited for the dataset of dermatological disorders, where class boundaries may not be as simple or easily separated.

4.1.3 Comparative analysis of the two strategies: The comparison between the One-vs-One and One-vs-All strategies reveals several key insights:

- The accuracy of the OvA strategy (98.74%) is higher than that of the OvO strategy (97.46%), demonstrating that the OvA approach is better able to handle the multiclass classification problem in this specific scenario.
- Both strategies exhibited high precision and recall, indicating that Logistic Regression is highly capable of correctly identifying both positive and negative instances, minimizing false positives and false negatives. However, the OvA approach has a slight edge with its higher precision (98.74% vs. 97.5%) and recall (98.8% vs. 97.5%).
- The OvA strategy's higher recall rate suggests that it is more effective at identifying all true positives across the classes, which is particularly important in a healthcare setting, where it is crucial to detect all instances of a particular dermatological disorder, even at the expense of some false positives.

4.1.4 Visual representation and implications: The results of the experimental analysis are visualized in Figure 2, where the comparison of accuracy, precision, and recall for both the One-vs-One and One-vs-All strategies is depicted. The figure demonstrates the superiority of the One-vs-All strategy across all metrics, making it the more suitable choice for this dataset.

The findings of this study suggest that Logistic Regression with the One-vs-All strategy offers a more robust and accurate approach for multiclass classification tasks in dermatology. The marginally higher performance of the OvA approach could be attributed to its ability to evaluate each class in the context of all others simultaneously, providing a more generalized model that performs better in terms of both classification accuracy and the detection of positive instances.

The OvA approach outperforms the OvO strategy in our dermatological disease classification task due to several key factors. Firstly, OvA trains one classifier per class against all others, allowing it to learn broader class boundaries. This is particularly effective in the Dermatology dataset, where some classes have relatively fewer instances and may not benefit from isolated pairwise comparisons as in OvO.

Secondly, OvA reduces the number of classifiers required compared to OvO, which can lead to lower computational complexity and better generalization, especially when the dataset is moderately sized. In contrast, OvO generates multiple classifiers for each pair of classes, which may lead to overfitting or inconsistent decisions due to conflicting votes in imbalanced or overlapping class distributions.

Finally, OvA classifiers typically produce calibrated probability scores, making it easier to select the final class with the highest confidence. In contrast, OvO relies on majority voting, which may be less robust in cases where class boundaries are not well separated. These factors collectively contribute to the superior performance of the OvA approach as observed in our results.

5. Conclusion and Real-World Implications

In conclusion, both One-vs-One and One-vs-All strategies demonstrate strong potential for automated classification of dermatological disorders, offering high accuracy and reliable performance. However, the One-vs-All strategy proved to be slightly more effective, especially in terms of accuracy, precision, and recall. This makes it the preferred approach for tasks where high classification performance is crucial, such as automated dermatology diagnostics in healthcare settings.

These findings reinforce the utility of Logistic Regression for healthcare applications and provide valuable insights for selecting the appropriate multiclass classification strategy based on the characteristics of the dataset. Further studies can explore additional strategies or hybrid approaches that combine the strengths of both One-vs-One and One-vs-All for even better performance.

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Biographical notes

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Dr. G. Ravi Kumar is an accomplished academic and researcher with a remarkable career in Computer Science & Technology. He completed his Master of Computer Applications at Sri Venkateswara University, Tirupati, AP, India, in 2001, and subsequently earned a Master of Philosophy in Computer Science and Technology from Sri Krishnadevaraya University, Anantapur, AP, India, in 2009. Driven by his passion for research, he pursued and completed his Ph.D. in Computer Science & Technology at Sri Krishnadevaraya University, Anantapur, AP, India, in 2014. Later, in 2020, he achieved a Master of Technology in Computer Science & Engineering from JNT University, Anantapur, AP.Since 2006, he has been an integral part of Rayalaseema University, Kurnool, AP, India, where he currently serves as an Assistant Professor and Coordinator in the Department of Computer Science. With an impressive 22 years of teaching experience, he has played a crucial role in nurturing young minds and shaping the next generation of scholars. A prolific researcher, his expertise is reflected in publishing more than 30 research papers in reputed international and national journals and conferences. Additionally, he has guided over 100 master-level projects, showcasing his commitment to fostering research and innovation. His primary research interests revolve around Software Engineering, Data Mining, Big Data Analytics, and Machine Learning, where he continues to make significant contributions to advancing knowledge and technology in these domains. His dedication to academia, extensive teaching experience, and substantial research achievements have solidified his reputation as a respected and influential figure in Computer Science and Technology.