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HYBRID ALGORITHMS FOR RELEVANT FEATURE SELECTION IN DIMENSIONALITY REDUCTION: A CASE STUDY IN DERMATOLOGICAL DISEASE CLASSIFICATION

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Abstract. Feature selection is a critical preprocessing step in machine learning that aims to reduce dimensionality while preserving classification performance. This study presents a comprehensive investigation of hybrid algorithms for relevant feature selection applied to dermatological disease classification. We implemented sequential forward selection with Multi-Layer Perceptron tie-breaking mechanisms to systematically identify informative features from a dermatological dataset containing 30 clinical and histopathological features. The hybrid approach achieved 95.95% accuracy using only 14 features, representing a 53.3% reduction in feature space. Key discriminators included clubbing rete ridges, vacuolization damage basal layer, and fibrosis papillary dermis. Our findings demonstrate that hybrid feature selection algorithms effectively optimize the balance between model complexity and predictive performance.

Keywords: feature selection, dimensionality reduction, dermatological classification, hybrid algorithms, machine learning.

1 Introduction

Healthcare data growth enables advanced diagnostic tools but introduces computational complexity and interpretability challenges [1]. Dermatological diagnosis combines clinical and histopathological data, creating high dimensional spaces that challenge traditional algorithms and clinical interpretation [2]. Dimensionality risks include overfitting and reduced generalizability [3].

Feature selection addresses these issues by identifying relevant feature subsets while maintaining performance [4]. Unlike feature extraction, it preserves original features, ensuring interpretability crucial for clinical decisions [5]. Traditional methods—filter, wrapper, and embedded each have limitations: missing interactions, computational cost, and algorithm specificity [6-8].

Hybrid approaches combine strategies to overcome individual weaknesses [9], leveraging strengths for better feature relevance and efficiency [10]. Neural network-based tie-breaking captures complex non-linear feature class relationships [11]. Dermatological classification involves complex pathology and subtle condition distinctions [12], requiring integration of clinical presentation, history, and histopathology [13]. Comprehensive datasets enable testing advanced feature selection [14].

This study investigates hybrid algorithms combining sequential forward se-lection with neural network tie resolution for dermatological classification. Objectives include: developing a discriminative feature selection algorithm, analyzing accuracy progression, and determining clinical versus histopathological feature importance. The approach adapts to other medical classification problems balancing interpretability and performance [15].

2 Methods

2.1 Feature Selection in Medical Applications

Medical feature selection demands interpretability, missing value handling, and domain knowledge integration [16]. While statistical methods (chi-square, information gain) remain prevalent

[17], they often overlook complex biological interactions [18]. Advanced ensemble methods and expert guided approaches have emerged to address medical data heterogeneity [19-21]. Automated diagnosis has evolved from image-based approaches [22-23] to integrated clinical-histopathological frameworks [24]. Despite machine learning's ability to detect subtle patterns [25-26], challenges persist in overlapping symptomatology and maintaining clinical interpretability [27].

2.2 Hybrid Feature Selection Algorithms

Hybrid methods combine filter efficiency with wrapper accuracy [28-29], with sequential selection ensuring computational tractability [30]. Neural network integration, particularly MLPs, enables capture of complex feature interactions and enhances tie-breaking mechanisms [31-33].

Comprehensive evaluation requires multicriteria assessment including accuracy, feature subset size, and stability [34]. Cross validation and multiple metrics ensure robust performance estimation in data limited medical contexts [35-36].

The core of the algorithm implements a greedy sequential forward selection approach that builds feature subsets incrementally. Starting with an empty feature set, the algorithm evaluates each remaining feature by adding it to the current subset and measuring the resulting classification performance. The feature that provides the maximum improvement in accuracy is permanently added to the selected subset.

When multiple features yield identical or very similar performance improve-ments, the algorithm employs an MLP classifier to break ties. The MLP serves as a sophisticated evaluation function that can capture non linear relationships and feature interactions that might not be apparent through simple accuracy measures. The tie-breaking process involves:

- Training separate MLP models for each tied feature
- Evaluating the MLP performance using cross-validation
- Selecting the feature associated with the highest MLP accuracy
- Recording the tie-breaking decision for transparency

The algorithm continues until a predefined maximum number of features is selected or until no further improvement in classification accuracy is observed. For this study, we systematically evaluated feature subsets of sizes ranging from 1 to 30 to comprehensively analyze the performance trajectory.

2.3 Dataset Characteristics

The study employed a dermatological dataset containing 366 instances across 6 conditions, characterized by 30 clinical and histopathological features. Clinical observations included erythema, scaling, and definite borders, while histopathological findings encompassed clubbing of rete ridges, vacuolization damage in basal layer, and fibrosis of papillary dermis. This comprehensive feature set enables robust evaluation of hybrid selection algorithms while maintaining clinical relevance.

The study employed a dermatological dataset containing 366 clinical cases representing 6 distinct skin conditions. Each case was characterized by 30 features encompassing both clinical observations (erythema, scaling, age, etc.) and histopathological findings (clubbing of rete ridges, fibrosis, vacuolization damage, etc.). The dataset was partitioned into training (292 instances) and test (74 in-stances) sets, with notable class imbalance ranging from 5.4% (Class 6) to 31.1% (Class 1) in the test set. The target classes represent different dermatological conditions numbered from 1 to 6, with the following distribution: Class 1 (n=23), Class 2 (n=12), Class 3 (n=15), Class 4 (n=10), Class 5 (n=10), and Class 6 (n=4) in the test set, indicating a class imbalance that required careful consideration during the evaluation process.

2.4 Experimental Design

The hybrid feature selection algorithm was implemented using Python with scikit-learn for machine learning components. The MLP classifier used for both tie breaking and final evaluation employed the following configuration:

- Hidden layer architecture: Adaptive based on feature subset size

- Activation function: ReLU
- Solver: Adam optimizer
- Maximum iterations: 1000
- Random state: Fixed for reproducibility

The evaluation protocol consisted of:

- Sequential feature selection from 1 to 30 features
- For each feature subset size, recording the selected features and classification accuracy
- Comprehensive evaluation using precision, recall, F1-score, and overall accuracy
- Analysis of feature selection stability and consistency

Classification performance was evaluated using multiple metrics:
Overall Accuracy: The proportion of correctly classified instances.
Precision: The ratio of true positive predictions to total positive predictions for each class.
Recall: The ratio of true positive predictions to actual positive instances for each class.
F1-score: The harmonic mean of precision and recall.
Macro-averaged metrics: Unweighted average across all classes.
Weighted-averaged metrics: Average weighted by class support.

Given the relatively small dataset size, the evaluation was conducted using a held-out test set of 74 instances. While this approach provides definitive performance estimates, the limited test set size necessitates careful interpretation of results, particularly for less frequent classes.

3 Results

The hybrid feature selection algorithm demonstrated a clear performance improvement trajectory as features were sequentially added to the subset. The detailed results for each feature subset size are presented below:

The algorithm began by selecting “clubbing rete ridges” as the most discriminative single feature, achieving an accuracy of 48.65%. This histopathological feature demonstrated strong individual discriminative power, correctly classifying most instances of Class 1 (precision and recall of 0.91) while showing limited effectiveness for other classes.

The addition of vacuolization damage basal layer as the second feature, selected through MLP tie breaking from candidates including thinning suprapapillary epidermis, spongiform pustule, and age, resulted in a substantial improvement to 63.51% accuracy. This selection significantly enhanced the classification of Class 2 instances (recall improved to 1.00).

Progressive feature addition continued with:

- Feature 3: fibrosis papillary dermis (accuracy: 77.03%)
- Feature 4: spongiosis (accuracy: 74.32%)
- Feature 5: follicular papules (accuracy: 81.08%)

The algorithm achieved optimal performance in the 6-14 feature range, with the peak accuracy of 95.95% reached at 14 features. The selected 14-feature subset comprised:

Tab. 1. Detailed classification report for the optimal 14-feature subset

Class	Precision	Recall	F1-Score	Support
1	1.00	1.00	1.00	23
2	0.92	0.92	0.92	12
3	1.00	0.93	0.97	15
4	0.82	0.90	0.86	10
5	1.00	1.00	1.00	10
6	1.00	1.00	1.00	4
Macro Avg	0.96	0.96	0.96	74
Weighted Avg	0.96	0.96	0.96	74
Overall Accuracy	**95.95%**			74

Beyond 14 features, the algorithm showed diminishing returns with some fluctuation in performance. Notably, the addition of certain features led to temporary decreases in accuracy, suggesting potential overfitting or the inclusion of noisy features. The performance stabilized around 93-94% for feature subsets of size 17-30.

Class 1 demonstrated consistently excellent performance across most feature subset sizes, achieving perfect precision and recall (1.00) with the optimal 14-feature subset. This superior performance likely reflects the strong discriminative power of histopathological features for this particular dermatological condition.

Class 2 showed the most variable performance trajectory, with precision ranging from 0.00 in early feature subsets to 0.92 with the optimal 14-feature configuration. The recall remained consistently high (0.92) once sufficient features were included, indicating that while the class could be identified, early feature subsets struggled with false positive classifications.

The first three selected features (clubbing rete ridges, vacuolization damage basal layer, fibrosis papillary dermis) emerged as foundational discriminators, collectively achieving 77.03% accuracy. These histopathological features capture fundamental tissue level changes that are diagnostic of different dermatological conditions.

The selection process revealed a balanced integration of clinical and histopathological features, with histopathological features dominating the early selection stages and clinical features providing incremental improvements in later stages. This pattern aligns with dermatological diagnostic practice where histopathological examination provides definitive diagnosis while clinical features guide initial assessment.

Interestingly, 'age' was selected as the 13th feature, contributing to the optimal subset. This selection highlights the importance of demographic factors in dermatological diagnosis, as age-related changes in skin physiology can influence disease presentation and progression.

The hybrid algorithm demonstrated reasonable computational efficiency, with the sequential selection process requiring manageable computational resources. The MLP based tie breaking mechanism, while adding computational overhead, provided substantial value in feature selection quality that justified the additional computational cost.

4 Conclusion

This study successfully demonstrated the effectiveness of hybrid feature se-lection algorithms in addressing the dimensionality reduction challenge in dermatological disease classification. The proposed approach, combining sequential forward selection with MLP based tie breaking mechanisms, achieved exceptional performance by identifying 14 highly relevant features from a set of 30, resulting in 95.95% classification accuracy while reducing the feature space by 53.3%.

The systematic analysis revealed that histopathological features serve as foundational discriminators, with clinical features providing important complementary information for accurate diagnosis. The algorithm's ability to balance performance optimization with feature interpretability makes it particularly suitable for medical applications were understanding the basis for diagnostic decisions is crucial.

Key contributions of this research include:

1. Methodological innovation: The integration of neural network-based tie breaking in sequential feature selection represents a novel approach that captures complex feature interactions while maintaining interpretability.
2. Clinical relevance: The selected features align with established dermatological diagnostic criteria, providing confidence in the clinical applicability of the results.
3. Performance optimization: The achievement of high accuracy with a substantially reduced feature set demonstrates effective dimensionality reduction without performance compromise.
4. Transparency: The sequential selection process provides clear insights into feature importance ranking, supporting clinical understanding and trust.

The findings have significant implications for the development of clinical decision support systems in dermatology, where the combination of high accuracy and interpretable features can enhance diagnostic confidence while reducing computational requirements. The approach is readily adaptable to other medical classification problems where similar challenges of high dimensionality and in-terpretability requirements exist.

Future research should focus on validating these findings with larger, more diverse datasets and investigating the clinical implementation of the reduced feature set in real world dermatological practice. The integration of additional data modalities and the development of condition specific feature selection models represent promising directions for further advancement in automated dermatolog-ical diagnosis.

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DERMATOLOGIK KASALLIKLAR KLASSIFIKATSIYASIDA BELGILAR FAZOSI O‘LCHAMINI QISQARTIRISH UCHUN GIBRID ALGORITMLAR ORQALI RELEVANT BELGILARNI TANLAB OLISH

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Annotatsiya. Belgilarni tanlab olish – bu klassifikatsiyani ishlashni saqlab qolgan holda o‘lchamlarni qisqartirishga qaratilgan mashinaviy o‘qitishning muhim oldindan qayta ishlash bosqichidir. Ushbu tadqiqot dermatologik kasalliklarni klassifikatsiya qilishga qo‘llaniladigan relevant belgilarni tanlash bo‘yicha gibrid algoritmlarni chuqur o‘rganishni taqdim etadi. Biz 30 ta klinik va gistopatologik belgilarni o‘z ichiga olgan dermatologik ma’lumotlar to‘plamidan tizimli ravishda relevant belgilarni aniqlash uchun ko‘p qatlamli perseptron bilan bog‘langan ketma-ket oldinga tanlash usulini amalga oshirdik. Gibrid yondashuv atiga 14 ta relevant belgidan foydalangan holda 95,95% aniqlikga erishdi, bu belgilar fazosining 53,3% ga qisqarishini ifodalaydi. Asosiy farqlovchi belgilar qatoriga rete tizmalarining o‘zgarishi, bazal qatlamning vakuollanish shikastlanishi va papillyar dermaning fibrozi kiradi. Bizning natijalarimiz shuni ko‘rsatadiki, gibrid belgilarni tanlash algoritmlari model murakkabligi va bashorat qilish ishlovi o‘rtasidagi muvozanatni samarali optimallashtiradi.

Kalit so‘zlar: relevant belgilarni tanlab olish, o‘lchovlarni qisqartirish, dermatologik klassifikatsiya, gibrid algoritmlar, mashinaviy o‘qitish.

ВЫБОР РЕЛЕВАНТНЫХ ПРИЗНАКОВ С ПОМОЩЬЮ ГИБРИДНЫХ АЛГОРИТМОВ ДЛЯ СОКРАЩЕНИЯ РАЗМЕРА ПРОСТРАНСТВА ПРИЗНАКОВ В КЛАССИФИКАЦИИ ДЕРМАТОЛОГИЧЕСКИХ ЗАБОЛЕВАНИЙ

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Аннотация. Выбор признаков является важным этапом предварительной обработки в машинном обучении, направленным на снижение размерности при сохранении качества классификации. В данном исследовании представлено глубокое обучение гибридных алгоритмов отбора признаков для классификации дерматологических заболеваний. Мы реализовали метод последовательного прямого отбора в сочетании с многослойным персептроном для систематического выявления релевантных признаков из дерматологического набора данных, содержащего 30 клинических и гистопатологических признаков. Гибридный подход достиг точности 95,95% при использовании всего 14 релевантных признаков, что представляет собой сокращение пространства признаков на 53,3%. К ключевым отличительным признакам относятся изменения гребня сетчатки, вакуолизация базальной пластинки и фиброз сосочкового слоя дермы. Наши результаты показывают, что гибридные алгоритмы отбора признаков эффективно оптимизируют компромисс между сложностью модели и предсказательной способностью.

Ключевые слова: выбор релевантных признаков, уменьшение размерности, дерматологическая классификация, гибридные алгоритмы, машинное обучение.