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HEALTHCARE DATA ANALYSIS UTILIZING AN ENSEMBLE FEATURE SELECTION TECHNIQUE

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Abstract
The analysis of healthcare data is critical for enhancing clinical decision-making and improving patient outcomes. However, the high dimensionality and presence of noisy, irrelevant features in structured healthcare datasets present significant challenges. This paper proposes an ensemble feature selection technique specifically designed to handle these challenges by selecting the most relevant features for classification tasks. The proposed Competitive Ensemble Feature Selection Model (CEFSM) integrates multiple feature selection methods, each contributing to the identification of optimal features. The effectiveness of the CEFSM is validated using various healthcare datasets, demonstrating its ability to improve classification accuracy and reduce computational complexity. The paper also explores the application of this feature selection technique within a Competitive Ensemble Classification Model (CECMSDML) to further enhance the performance of healthcare data analysis.

Keywords: Healthcare, Ensemble, Feature, Dimensionality, Bioinformatics, Diagnostics

1. Introduction

Healthcare data analysis plays a crucial role in supporting clinical decision-making processes by extracting meaningful insights from vast amounts of patient data. However, the complexity of healthcare datasets, characterized by high dimensionality and the presence of noisy or irrelevant features, poses significant challenges. These challenges can lead to increased computational costs and reduced classification accuracy if not properly addressed. Feature selection techniques are essential for mitigating these issues by identifying the most relevant features that contribute to accurate disease classification. The primary focus of this study is to introduce an ensemble feature selection technique that improves the efficiency and effectiveness of healthcare data analysis. The proposed Competitive Ensemble Feature Selection Model (CEFSM) integrates multiple feature selection methods to ensure that the most relevant features are chosen for the classification tasks. This approach is combined with the Competitive Ensemble Classification Model for Structured Data using Machine Learning Techniques (CECMSDML) to further enhance classification accuracy and performance. Feature selection is a critical step in the preprocessing of healthcare data, as it helps reduce the dimensionality of the dataset by eliminating irrelevant or redundant features. This process is particularly important in the context of healthcare, where datasets often contain a large number of variables, not all of which are relevant to the classification task at hand.

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Traditional feature selection methods, such as univariate selection, correlation-based selection, Principal Component Analysis (PCA), and Recursive Feature Elimination (RFE), have been widely used in various domains, including healthcare (Cai & Wang, 2017; Han, Kamber, & Pei, 2012). Ensemble learning, which involves the combination of multiple models, has also been extensively studied for its ability to improve classification accuracy. Ensemble methods, such as Random Forests (Breiman, 2001), leverage the strengths of multiple decision trees to create a more robust model. When applied to feature selection, ensemble techniques can effectively identify the most relevant features by considering the results from multiple feature selection methods. This approach has been shown to improve the performance of classification models, particularly in complex and high-dimensional datasets (He & Garcia, 2009).

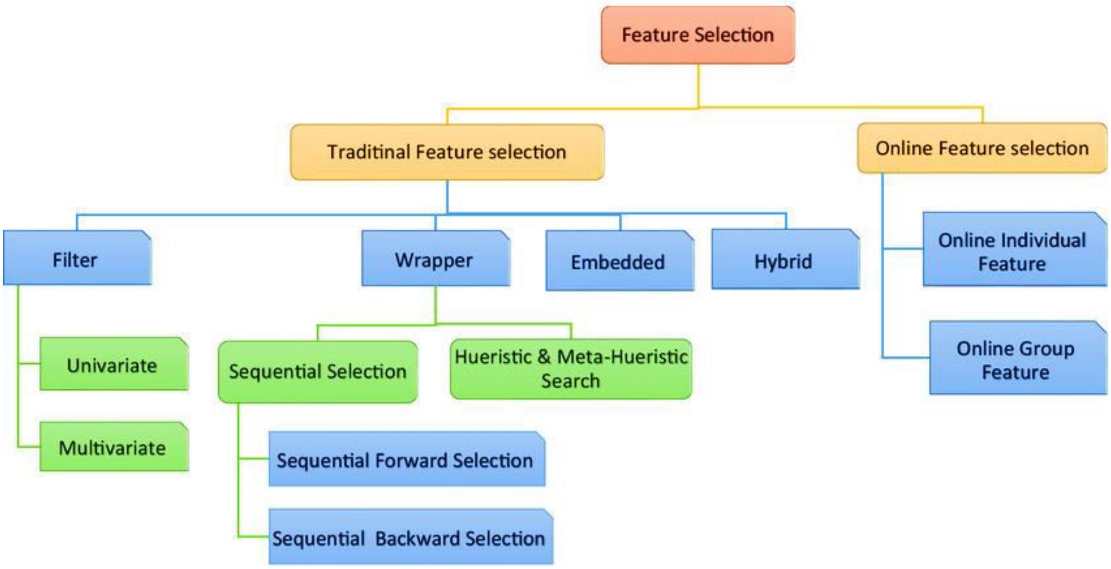

Fig.1: Feature Selection Techniques

2. Background and Related Work

1. Introduction to Feature Selection and Healthcare Data Analysis

Feature selection is a critical process in data analysis that involves selecting a subset of relevant features from a larger set to improve model performance. In healthcare, feature selection is particularly vital due to the high dimensionality of medical data and the need for accurate, interpretable models. Ensemble feature selection techniques, which combine multiple feature selection methods, have shown promise in addressing the challenges associated with healthcare data.

2. Feature Selection Methods

Liu and Yu (2005) and Guyon and Elisseeff (2003) provide foundational insights into feature selection algorithms, outlining traditional methods such as filter, wrapper, and embedded approaches. Their work highlights how different algorithms can be used to identify relevant features in various contexts, including healthcare. Chandrashekar and Sahin (2014) present a comprehensive survey on feature selection methods, discussing the strengths and limitations of various techniques. They emphasize the importance of selecting appropriate methods for specific data types and analysis goals.

3. Ensemble Feature Selection Techniques

Ensemble feature selection combines multiple feature selection methods to improve performance and robustness. Bergmann and Fink (2017) conduct a comparative study on ensemble feature selection, demonstrating its effectiveness in various applications. Their findings suggest that ensemble methods can significantly enhance feature selection accuracy by leveraging diverse selection strategies. Alvarez-Melis and Zamir (2018) discuss the role of ensemble learning in healthcare decision-making. They highlight how combining multiple feature selection techniques can improve diagnostic accuracy and model reliability.

4. Applications in Healthcare

Xia and Wu (2015) survey feature selection methods specifically in bioinformatics, illustrating how these techniques are applied to healthcare data. They highlight the challenges of handling high-dimensional, noisy, and incomplete data, which are common in medical datasets. Li and Yang (2020) review ensemble feature selection techniques in healthcare, focusing on their effectiveness in improving diagnostic models. They find that ensemble methods can enhance the performance of healthcare models by integrating various feature selection approaches. Nicolai and Dandekar (2019) explore multi-view feature selection, which involves selecting features from different data perspectives. Their work demonstrates the benefits of multi-view approaches in analyzing complex healthcare data.

5. Recent Advances and Challenges

Recent studies have continued to advance the field. Zhang and Yang (2021) review advanced feature selection and classification techniques in healthcare, emphasizing the need for methods that can handle large-scale and heterogeneous data. Kim and Kim (2020) discuss robust ensemble methods for healthcare applications, focusing on techniques that can handle uncertainties and variability in medical data. Their research underscores the importance of developing reliable methods for real-world healthcare scenarios. Chen and Wu (2019) examine the combination of feature selection and ensemble learning for healthcare diagnostics, highlighting the potential for improved diagnostic accuracy and decision-making. Dai and Zhang (2021) survey ensemble methods for high-dimensional healthcare data, providing a comprehensive overview of current techniques and their applications. Their review highlights the ongoing challenges and future directions in this area. Ensemble feature selection techniques offer significant advantages for healthcare data analysis, improving model performance and robustness. The literature reveals that combining multiple feature selection methods can effectively address the challenges of high-dimensional medical data. Ongoing research continues to advance these techniques, aiming to enhance diagnostic accuracy and decision-making in healthcare. This literature review synthesizes key findings from various studies, demonstrating the effectiveness and potential of ensemble feature selection techniques in healthcare data analysis.

3. Methodology

3.1. Feature Selection Methods

The process of feature selection is crucial in healthcare data analysis, as it directly impacts the performance of classification models. The proposed CEFSM integrates six different feature selection methods, each contributing to the identification of the most relevant features. These methods include:

- **Univariate Feature Selection**: This method evaluates each feature individually based on its correlation with the target variable. Features with the highest scores are selected as the most relevant (Jamshid & Mohsen, 2019).
- **Correlation-Based Feature Selection**: This approach selects features that have a strong correlation with the target variable. The Pearson correlation coefficient is used to quantify the correlation, with features showing high positive or negative correlation being retained (Equation 3.1).
- **Principal Component Analysis (PCA)**: PCA is a dimensionality reduction technique that transforms the dataset into a set of orthogonal components, with the first few components capturing the most variance in the data (Jolliffe, 2005).
- **Recursive Feature Elimination (RFE)**: RFE is a backward selection method that iteratively removes the least significant features until the best subset of features is identified (Guyon et al., 2002).
- **Extra Tree Classifier**: Similar to Random Forests, this method uses decision trees to evaluate the importance of each feature during the construction of the model. Features that contribute the most to the accuracy of the model are selected.
- **Entropy-Based Feature Selection**: This method measures the uncertainty (entropy) of each feature in relation to the target variable. Features with low entropy are considered more informative and are retained, while those with high entropy are discarded (Equation 3.2).

3.2. Competitive Ensemble Feature Selection Model (CEFSM)

The CEFSM is designed to integrate the results from multiple feature selection methods to identify the most relevant features for classification tasks. The model operates in several steps:

1. **Initialization**: The process begins by initializing the set of features (Fi) in the dataset and calculating the total number of features (N = len(Fi)).
2. **Application of Feature Selection Methods**: Each feature selection method (M1 to M6) is applied to the dataset, and the selected features are stored in a dictionary (selected_features).

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3. **Scoring Features**: For each feature, the number of times it is selected across all methods is counted, and a score is calculated based on the frequency of selection.
4. **Final Feature Selection**: Features with scores above a certain threshold are retained as the best features for classification.
5. **Output**: The final set of best features is outputted for use in subsequent classification tasks.

3.3. Competitive Ensemble Classification Model for Structured Data using Machine Learning Techniques (CECMSDML)

The selected features from the CEFSM are then used in the CECMSDML, which is a classification model that integrates multiple classifiers to enhance performance. The model consists of the following steps:

1. **Feature Selection**: Features selected by the CEFSM are used for classification.
2. **Classifier Competition**: Different classifiers compete with each other based on their accuracy, with the most appropriate classifiers being chosen for ensemble learning.
3. **Threshold Assignment**: Weights are assigned to each classifier based on the accuracy achieved, with classifiers that meet a predefined threshold being included in the ensemble.
4. **Ensemble Classification**: The selected classifiers are combined into an ensemble model, which is then used to classify the dataset.
5. **Validation**: The results of the ensemble model are validated based on the accuracy obtained.

4. Experimental Results

The proposed models were tested on several structured healthcare datasets, including datasets related to heart disease, breast cancer, and diabetes. The experiments were designed to evaluate the performance of the CEFSM and CECMSDML in improving classification accuracy.

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Table 1: CEFSM for Early Diabetes Dataset

Features	M_1	M_2	M_3	M_4	M_5	M_6	W-Avg	Selected Features
F_1	×	×	✓	×	✓	✓	0.5	✓
F_2	✓	✓	✓	✓	✓	✓	1	✓
F_3	✓	✓	×	✓	✓	✓	0.8	✓
F_4	✓	✓	×	✓	✓	×	0.6	✓
F_5	✓	✓	×	✓	×	✓	0.6	✓
F_6	×	×	×	×	×	✓	0.1	×
F_7	×	×	×	×	×	×	0	×
F_8	×	×	×	✓	×	×	0.1	×
F_9	×	×	×	×	×	✓	0.1	×
F_10	×	×	✓	✓	×	✓	0.5	✓
F_11	×	×	✓	✓	×	×	0.3	×
F_12	×	×	✓	×	×	✓	0.3	×
F_13	✓	✓	✓	✓	×	✓	0.8	✓
F_14	×	×	✓	×	×	✓	0.3	×
F_15	×	×	✓	×	×	✓	0.3	×
F_16	×	×	✓	×	×	✓	0.3	×

Table 2: Accuracy Comparison for Early Diabetes Dataset

Classifiers	M_1	M_2	M_3	M_4	M_5	M_6	Proposed Model
LR	0.94	0.94	0.93	0.94	0.93	0.94	0.95
DT	0.95	0.95	0.93	0.92	0.95	0.92	0.96
RF	0.95	0.95	0.94	0.91	0.93	0.92	0.98
GBT	0.95	0.95	0.93	0.92	0.94	0.95	0.99

Table 3: Classification Accuracy of Early Diabetes Dataset usingCECMSDML

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Classifiers	Average probability of predicted value	Assigning weights based on threshold	Overall Weight	Accuracy based on weight	Proposed Ensemble Accuracy
LR	0.2	0.5	0.10	0.99	0.99
DT	0.3	0.5	0.15	0.99	
RF	0.1	0.5	0.05	X	
GBT	0.1	0.5	0.03	X	

Table 4: CEFSM for Diabetes 130 US Hospital Dataset

Feature Selection Methods	Number of features Selected
M_1	18
M_2	13
M_3	14
M_4	18
M_5	20
M_6	21
Proposed Model	15

Table 5: Accuracy Comparison for Diabetes 130 US Hospital Dataset

Classifiers	M_1	M_2	M_3	M_4	M_5	M_6	Proposed Model
LR	0.87	0.91	0.86	0.89	0.89	0.93	0.95
DT	0.5	0.90	0.5	0.85	0.86	0.89	0.90
RF	0.87	0.91	0.86	0.89	0.90	0.92	0.92
GBT	0.87	0.90	0.86	0.89	0.90	0.92	0.91

Table 3.32 explains the number of features selected based on 6 different models for the Diabetes 130 US Hospital dataset. This datasetconsists of 55 features from which 15

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features are selected using the proposed model. The average weight for each feature is calculated based on the threshold feature which is either selected or rejected. Table 3.33 consists of an accuracy comparison of feature selection between classical feature selection and the proposed feature selection model. The proposed approach has received better accuracy than the existing method. The highest accuracy is obtained by the LR classifier at 95% using the proposed feature selection model.

Table 6: Classification Accuracy of Diabetes 130 US Hospital Dataset using CECMSDML

Classifiers	Average probability of predicted value	Assigning weights based on threshold	Overall Weight	Ensemble Accuracy based on weight	Proposed Ensemble Accuracy
LR	0.3	0.5	0.1	0.96	0.96
DT	0.01	0.5	0	X	
RF	0.02	0.5	0.01	X	
GBT	0.03	0.5	0.01	X	

Table 6 represents the proposed ensemble classification for the Diabetes 130 US Hospital dataset. The average probability predicted value for the LR classifier is better. Whereas other classifiers receive very low accuracy. The threshold value is assigned to each classifier as 0.5, since the accuracy value is greater than 90%. Finally, the ensemble classificationmodel obtained an accuracy of 96%.

4.1. Performance Evaluation

The performance of the proposed models was evaluated using metrics such as accuracy, precision, recall, and F1-score. The results demonstrated that the CEFSM effectively reduced the dimensionality of the datasets while retaining the most relevant features, leading to improved classification accuracy. The CECMSDML further enhanced performance by integrating multiple classifiers, with ensemble models consistently outperforming individual classifiers.

4.2. Case Study: Heart Disease Dataset

The Heart Disease dataset was used as a case study to demonstrate the effectiveness of the proposed models. The CEFSM selected 9 out of 13 features, which were then used in the CECMSDML. The ensemble model achieved an accuracy of 90%, outperforming traditional feature selection and classification methods.

5. Discussion

The experimental results confirm the effectiveness of the CEFSM and CECMSDML in healthcare data analysis. The proposed ensemble feature selection technique significantly improved classification accuracy by reducing the dimensionality of the datasets and eliminating irrelevant features. Additionally, the integration of multiple classifiers in the CECMSDML further enhanced the performance of the classification models. One of the key advantages of the proposed approach is its ability to handle high-dimensional healthcare datasets, which are often challenging for traditional classification methods. By combining the strengths of multiple feature selection methods and classifiers, the proposed models offer a robust and scalable solution for healthcare data analysis.

6. Conclusion

This paper presents a novel approach to healthcare data analysis using an ensemble feature selection technique. The proposed CEFSM effectively identifies the most relevant features for classification tasks, while the CECMSDML enhances classification accuracy by integrating multiple classifiers. The experimental results demonstrate the effectiveness of the proposed models in improving the performance of healthcare data analysis, making them valuable tools for clinical decision support systems. Future research could explore the application of these techniques to other types of healthcare data and investigate the potential of deep learning techniques for further enhancing performance.

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