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Comparative Analysis of the Performance of Feature Selection Methods in Diabetic Retinopathy Prediction Using Multilayer Perceptron Model

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Abstract— Diabetic Retinopathy (DR), a leading cause of visual impairment among working-age adults, is increasing globally, necessitating effective predictive tools. Machine learning (ML) classifiers often struggle with high-dimensional datasets, making feature selection (FS) critical for improving predictive performance. This study evaluates the impact of FS techniques on the performance of an ML model for DR prediction using the MESSIDOR retinal dataset. Two FS methods, forward selection and variance threshold, were compared alongside a multilayer perceptron (MLP) classifier. The results showed that forward selection significantly enhanced MLP accuracy to 77.06%, outperforming the raw dataset (75.32%) and variance threshold (73.16%). The findings underscore the importance of appropriate FS in developing robust ML models. Integrating such models into clinical workflows could enhance early DR diagnosis, facilitate timely treatment, and reduce the risk of severe visual impairment, ultimately improving patient outcomes and healthcare efficiency.

Keywords/Index Terms—Comparison, Diabetic retinopathy, Dimensionality reduction, Machine learning, Prediction

1. Introduction

Among the human sensory organs, the eye is the most critical for interpreting the environment's structure (Bruce et al., 2014). However, it is particularly susceptible to complications from metabolic disturbances like diabetes, which affects millions of people globally. Diabetes mellitus develops when the body's ability to regulate blood glucose levels is impaired due to insufficient insulin production (Roglic, 2016; Rahman *et al*., 2021). This condition affects multiple organs, including the retina, heart, kidneys, and nerves. As of 2022, the population of people affected by diabetes has significantly increased to an estimated 830 million from the initial 108 million in 1980 (Mohammad *et al*., 2022) and is projected to be 1.3 billion by 2050 (Halsey, 2023). Among the complications of diabetes is diabetic retinopathy (DR), which is the leading cause of blindness in individuals under 50 (Dubey and Lohiya, 2021; Teo *et al*., 2021). Diabetic retinopathy manifests through retinal lesions such as microaneurysms, haemorrhages, and exudates. Microaneurysms are small red dots that serve as the earliest visible signs of DR. Haemorrhages appear as more prominent spots, while hard exudates and soft exudates present as bright yellow and white spots, respectively, due to plasma leakage and nerve fibre swelling (Wejdan *et al*., 2020). DR progresses through damage of capillaries and microvasculature to the retina's blood vessels caused by prolonged high blood sugar levels, ultimately leading to irreversible vision loss if untreated (Kropp et al., 2023).

DR is classified into two stages: Non-Proliferative and Proliferative. Non-Proliferative DR involves swelling and blockage of retinal blood vessels, while Proliferative DR, a more advanced stage, is characterised by abnormal blood vessel growth, increasing the risk of vision loss (Bhardwaj *et al*., 2021; Kaur *et al*., 2008).

Early detection via routine screening is essential for preventing permanent retinal damage, as it allows for timely intervention through treatments such as laser therapy, anti-VEGF injections, or surgery, which can significantly reduce the risk of vision loss (Kollias and Ulbig, 2010). Recent advances in medical technology have revolutionised diagnostic procedures, transitioning from manual methods to computer-aided diagnosis (CAD) systems. These systems, integrated with artificial intelligence (AI) and machine learning (ML) enable automated analysis of retinal fundus images for lesion detection, vessel segmentation, and optic disk analysis (Nurul *et al*., 2022).

Despite the technological advancements, the high dimensionality of medical image datasets poses a significant challenge to ML models, often compromising their accuracy and effectiveness (Sourabh *et al*., 2021). Feature selection (FS) methods can address this issue by identifying relevant features with strong predictive power, improving model accuracy and efficiency while reducing computational costs and the risk of overfitting (Pudjihartono *et al*., 2022; Folorunsho & Du Toit, 2023).

This study aims to analyse the performance of feature selection methods in predicting DR comparatively using the MLP model, identifying the most compelling feature selection method and its impact on prediction accuracy. The objectives of this include:

1. To design a DR prediction model incorporating different FS techniques and the MLP classifier.
2. To implement the designed model using the pre-processed MESSIDOR retinal dataset.
3. To evaluate the performance of the model across three scenarios: no feature selection, forward selection, and variance threshold, using standard metrics such as accuracy, precision, recall, and F1-score.

The findings of this research extend prior studies by providing a comparative analysis of FS methods in the context of DR prediction, thereby contributing to the optimisation of diagnostic systems for this condition. The ultimate goal is to enhance the early detection and management of DR, particularly in diabetic patients at risk of severe complications. As diabetes prevalence continues to rise globally, developing robust ML models for DR prediction has become a critical healthcare priority.

The remainder of the paper is organised as follows: The methodology of the predictive model is presented in Section II. Section III provides the results and discussion. Section IV outlines the study limitations, and finally, the paper is concluded in Section V.

2. Methodology

In this section, the various steps employed in this study to improve the detection of DR using two FS techniques and an MLP are described. It provides the details of the dataset used, the FS methods, the model selection process, and the evaluation metrics.

2.1. Data Description

The dataset used in this study is derived from the MESSIDOR image-based, which is globally recognised in DR research. The data have been preprocessed and normalised; it comprises 19 numerical features representing various characteristics extracted from retinal images alongside a binary label indicating the presence or absence of DR. There are 1151 samples in the dataset. The dataset was split into two subsets: 80% for training and the remaining 20% is reserved for evaluation.

2.3. Variance Threshold

The threshold variance is a simple, efficient filter-based FS technique that eliminates low-variance features. Implicitly, this means the variance in one variable over samples carries very minimal or no contribution toward a model's predictive power (Van Hulse *et al*. 2012). In threshold variance, the variance of every feature is computed beyond which those lying below the threshold value get deleted. The method helps reduce the problem of overfitting by reducing the dimensionality of a dataset; this reduces computational complexity and maintains only features with a certain degree of variability to be retained for further processing. It is very efficient at the pre-processing stage in high-dimensional datasets, given that it removes redundant or irrelevant features fast without depending on any particular ML model (Zebari *et al*. 2020).

Most of the datasets related to DR prediction contain features with negligible variability, such as constant or near-constant values across samples. Therefore, it adds noise and reduces model performance. Variance thresholding will ensure that only the features with meaningful variability remain, making the dataset more compact and informative.

2.4. Forward Selection

Forward selection is a wrapper FS method used to identify relevant features from large datasets. It is a sequential technique that improves the performance of ML models by iteratively adding the most significant features to the model (Reif and Shafait, 2014). The algorithm starts with an empty feature set and checks each feature individually regarding its contribution toward the target variable, usually defined based on a performance measure. This adds the best-improving feature to the model. This process continues until no further improvements are detected or a stop criterion is reached. Forward selection diminishes the dimensionality of datasets, reduces overfitting, and makes models more interpretable by choosing the most relevant features.

Diabetic retinopathy datasets are mostly complex and high-dimensional, carrying some irrelevant or redundant features that could make it tricky for the model to behave well; therefore, forward selection creates an avenue for analysis down to the most critical features. Since it reduces computational complexity, this positively affects efficiency and improves the accuracy of the developed model (Najafabad *et al*. 2015). Moreover, FS enhances interpretability, which is vital in medical applications, as the relationship between predictors and outcomes could provide clinicians with valuable insights (Banegas-Luna *et al*. 202; Goriparthi, 2022). Forward selection guarantees that only the most predictive features of the model, precisely the retinal characteristics or biomarkers of the patient, are included, making it more robust and reliable.

2.5. Multilayer Perceptron

The MLP is a feedforward artificial neural network (ANN), completely connected, and tends to provide an output for some input signals. It contains several hidden layers between the input and output layers. The MLPs are common in ML and data analysis because they can solve complex nonlinear problems (Abiodun *et al*. 2019). The number of hidden layers required varies depending on the requirements of the predictive task at hand. In the context of DR detection, MLPs can be used to classify retinal images based on the presence and severity of DR. The effectiveness of an MLP in DR detection relies on its ability to learn from the vast and varied features present in retinal images (Islam *et al*. 2020). Hidden layers in the MLP apply activation functions such as ReLU (Rectified Linear Unit) or sigmoid to the weighted sums of inputs, enabling the network to model complex relationships between features. For example, the network can learn to identify microaneurysms, haemorrhages, and exudates in retinal images, key indicators of DR. The output layer of the MLP then produces a prediction, which could be a classification of the DR stage or a probability score indicating the likelihood of DR being present (Sadhana *et al*. 2020). A schema of the typical diagram of an MLP is illustrated in Figure 1.

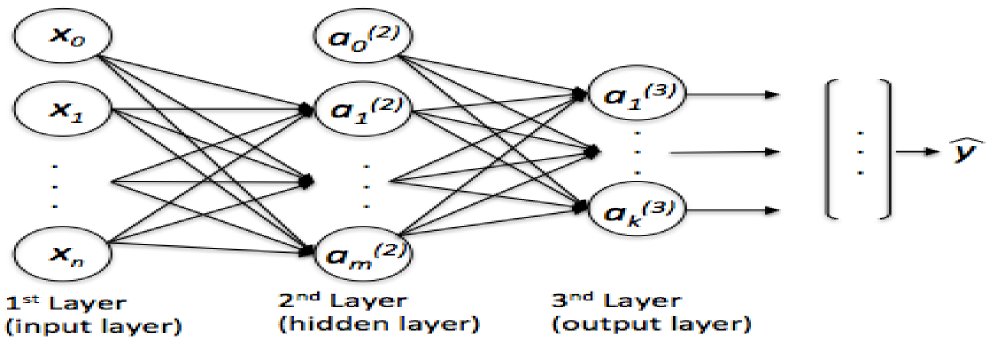

Figure 1. Schema of a Multilayer Perceptron

Given an n-dimensional input vector of any layer of the MLP, it produces a k-dimensional output vector, $f(x): \mathbb{R}^n \rightarrow \mathbb{R}^k$, and the input to the MLP is a vector $\boldsymbol{x} \in \mathbb{R}^{n_z}$.

The output of each processing unit can be expressed as in Equation (1):

$$f(x) = \boldsymbol{\Phi}\left(\sum_j \boldsymbol{w}_j \boldsymbol{x}_j + \mathbf{b}\right) \qquad (1)$$

where the $\boldsymbol{x}_j$, $\boldsymbol{w}_j$, $\boldsymbol{\Phi}$ and $\mathbf{b}$ are the inputs, weights, nonlinear activation function and bias.

The justification for using MLP to detect DR is that it can effectively handle such complex, high-dimensional medical datasets (Shirwaikar *et al*. 2019). Being a feedforward ANN, MLP can model nonlinear relationships between input features, an essential aspect in analysing medical imaging data and other diagnostic features of DR. Literature studies have shown that, if appropriately trained for any given task, the capability of MLP to generalise would therefore be excellent when clinical and imaging data of diversity were integrated. Moreover, it allows fine-tuning within its architecture for specificity towards specific tasks with highly comparable performance metrics in terms of sensitivity and specificity versus other traditional machine learning algorithms. It makes MLP an interesting option for DR detection, particularly for explainability and scalability (Rajarajeshwari and Selvi, 2024).

2.6. Performance Evaluation

The following are the definitions of the performance metrics used to evaluate the performance of the model developed:

1) *Accuracy (AC):* The accuracy refers to the ratio of correctly classified instances relative to total sample cases:

$$\text{AC} = \frac{TP+TN}{TP+TN+FP+FN}. \quad (2)$$

2) *Recall:* The recall is defined as the percentage of actual positive cases correctly classified:

$$Recall = \frac{TP}{TP+FN}. \quad (3)$$

3) *Precision:* The precision measures the ratio between correctly classified instances and positive predictions made by a model:

$$\text{Precision} = \frac{TP}{TP+FP}. \quad (4)$$

4) *F1 Score:* The F1 score is the harmonic mean of both the precision and the recall:

$$F1 = 2\left(\frac{Precision*Recall}{Precision+Recall}\right). \quad (5)$$

5) *Area Under the Receiver Operating Characteristic Curve (AUC-ROC):* The AUC-ROC measures the area under the ROC curve which depicts tradeoff between sensitivity (or recall) and specificity at different classification thresholds.

$$AUC = \int_0^1 TPR(t)d(FPR(t)) \quad (6)$$

.

3. Results and Discussion

The proposed model was implemented and tested on a Personal Computer (PC) equipped with an Intel(R) Core(TM) i3-2350M CPU @ 2.60GHz processor, 8 GB of RAM, and a 64-bit operating system. The developed model was built on Google Colaboratory and incorporated the variance threshold Filter (a FS method), forward selection (a wrapper FS method), and the MLP for DR prediction.

The pre-processed MESSIDOR image-based dataset was collected from the Kaggle Repository. The sample data consisted of 1,151 instances, of which 611 represented DR cases, and 540 were normal, with 19 numeric attributes. The training dataset included 483 (52.5%) of DR cases and 437 (47.5%) normal cases. After applying the variance threshold and forward selection separately, the number of attributes was reduced to eight and ten, respectively.

The system was evaluated on the testing dataset, consisting of 231 instances, including 128 DR cases and 103 non-DR cases under three scenarios: (1) without applying any feature selection, (2) using the variance threshold method, and (3) using the forward selection method. The confusion matrices generated for these three scenarios are presented in Figures 2a–c.

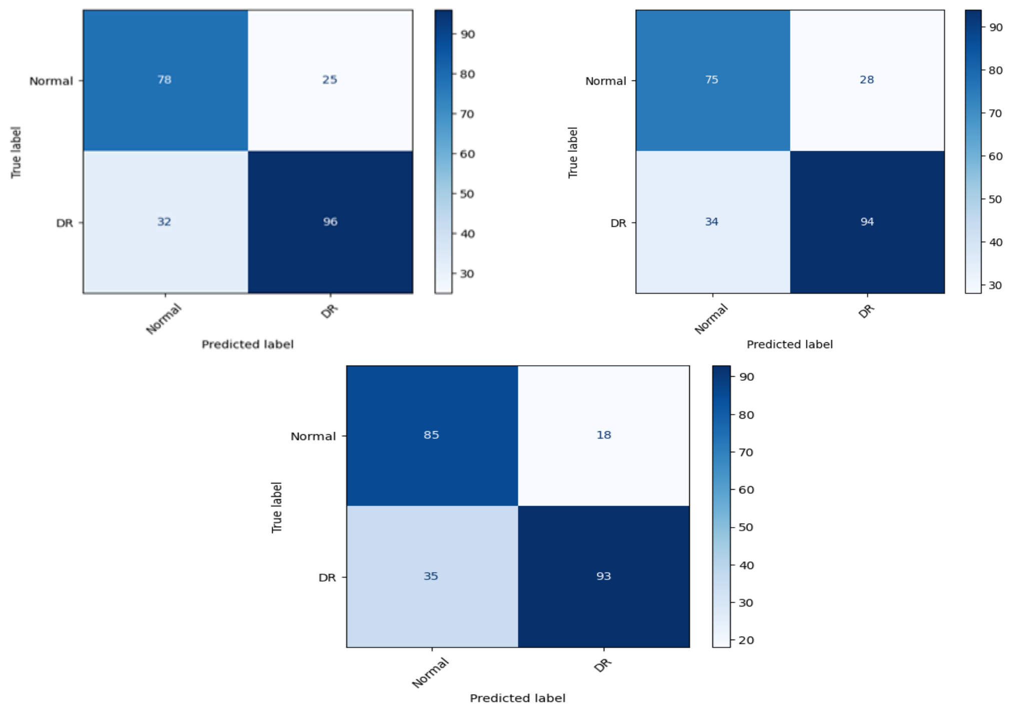

Figure 2. Confusion matrix for (a) no FS (b), variance threshold, (c) forward selection

The confusion matrices presented in Figure 2 were used to derive the corresponding performance metrics of the three FS methods presented in Table 1, and their visualisation is summarised in Figure 3. The visualisation gives insight into how the preselected features influenced the classification outcome of the multilayer perceptron model.

Table 1. Performance of three feature selection methods against MLP

Feature Selection Method	**Selected Feature**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**ROC-AUC (%)**
No Feature Selection	19	75.32	75.12	75.36	75.17	75.36
Variance Threshold	8	73.16	72.93	73.13	72.98	73.13
Forward Selection	10	77.06	77.31	77.59	77.03	77.59

Table 1 and Figure 3 revealed that without FS, the MLP model incorporated all 19 features, achieving an accuracy of 75.32% and an ROC-

AUC of 75.36%. While this approach included all available information, the results suggest that some features may have needed to be more relevant, slightly hindering overall performance. The variance threshold method reduced the feature set to 8 features, achieving slightly lower accuracy (73.16%) and ROC-AUC (73.13%). This aligns with Sourabh *et al*. (2021), highlighting the variance threshold as an effective baseline FS method, but it may only sometimes capture the most discriminative features for classification tasks. Forward selection selected 10 features from the DR dataset with the best accuracy, 77.06%, and ROC-AUC, 77.59%. It confirms the studies carried out by Braham *et al*. (2022), in which it was concluded that FS identifies the features in a dataset most predictively and improves the model's performance.

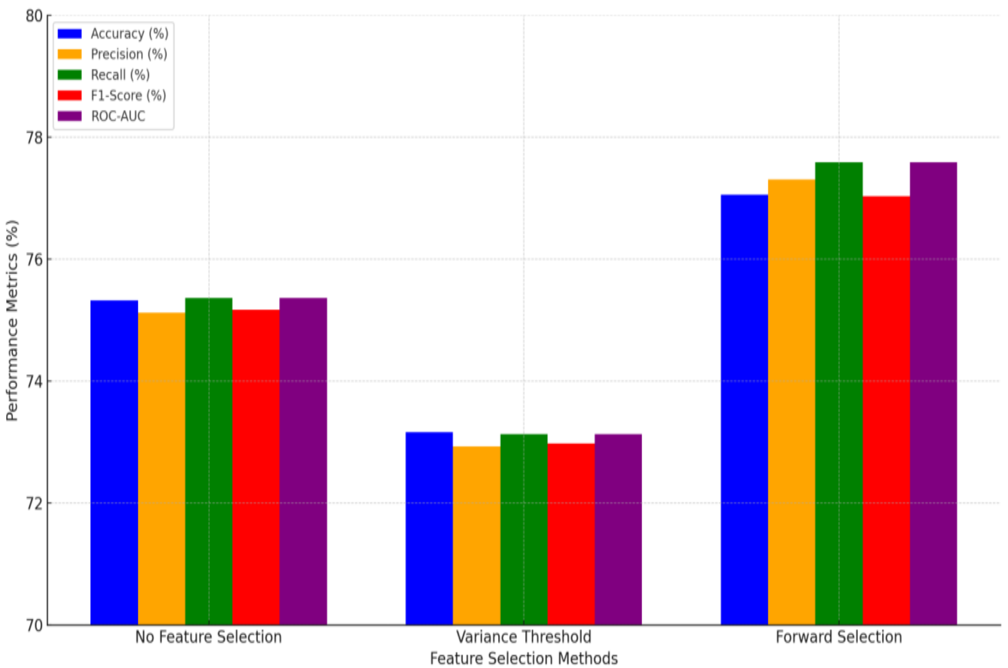

Figure 3. The visualisation of the three feature selection methods against MLP

The visualisation in Figure 3 highlights the superior performance of forward selection compared to the other two methods. Literature supports the use of forward selection for feature subset optimisation, emphasising its ability to balance dimensionality reduction and predictive accuracy while minimising overfitting (Zhang *et al*., 2020). On the other hand, the variance threshold method is helpful for quick dimensionality reduction but may overlook features with low variances that are still predictive.

The results demonstrate the critical role of FS in improving the performance of machine learning models for diabetic retinopathy prediction. Forward selection emerged as the most effective method in this study, improving all performance metrics compared to the other approaches. This finding underscores the importance of carefully selecting features to maximise predictive power while avoiding overfitting and reducing computational complexity.

These findings align with the broader consensus in feature selection research. Feature selection methods, such as forward selection, have enhanced model interpretability, reduced dimensionality, and improved classification metrics (Guyon and Elisseeff, 2003). Conversely, while more straightforward methods like variance threshold can simplify datasets, they are less robust in retaining the most critical predictive features (Bolón-Canedo e*t al*., 2015). However, it is important to consider the strengths and limitations of the proposed model. One of the strengths is that the study thoroughly evaluated different FS techniques and their impact on the MLP model. Including simple and advanced methods provides valuable insights into their effectiveness in improving model performance. Additionally, the study uses the publicly available MESSIDOR dataset and well-documented ML method, which ensure that other researchers can easily reproduce and further explore the findings. The wrapper FS method, while effective, is computationally expensive. This limitation could pose challenges in real-world applications where computational resources are limited or real-time processing is required.

4. Limitations

Although this study has demonstrated the capability of feature selection methods, especially forward selection, in improving the performance of the MLP model for diabetic retinopathy prediction, some limitations exist. First, in this study, only one dataset-MESSIDOR-was used; though well-established, it may not fully represent the diversity of real-world data regarding variations in imaging conditions, population demographics, or data from different healthcare settings. Second, the feature selection methods used forward selection and variance threshold do not represent the broad spectrum of existing FS techniques. Other methods, like mutual information or embedded FS methods, could provide additional insights into feature importance and predictive performance. Third, the MLP model was selected as the only classifier for this analysis. Although promising, their implementation gives further scope of their results with other robust classifier implementations, such as CNNs, since their whole dataset is image-based. Improvements discussed here and addressing these limitations could develop better generalisability with more robust predictive models dealing with diabetic retinopathy, among other medical conditions.

5. Conclusion

This study explores the MLP model in predicting DR through various feature selection methods, such as variance threshold and forward selection. The findings demonstrated that FS, mainly through forward selection, a wrapper selection method, significantly enhances model performance and improves the accuracy and robustness of the detection system. The success of this method highlights its potential for broader application in medical diagnostics, where accurate and efficient detection of conditions is critical. Despite the study's limitations, the results provide a strong foundation for future research to develop more effective diagnostic tools for diabetic retinopathy and other medical conditions. In conclusion, this work contributes to the field of medical image analysis by demonstrating how ML can be leveraged to improve the detection of DR. The methodologies developed and tested in this study offer promising pathways for improving the accuracy and reliability of automated diagnostic systems, ultimately benefiting clinical practice and patient outcomes.

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