RESEARCH ARTICLE

Empirical Analysis of the Performance of Machine Learning Algorithms in Classifying 2D MR Images from PCA Reduced HOG and LBP Features

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Abstract

This study investigates the role of feature extraction and dimensionality reduction techniques in addressing high-dimensional image data, with a particular focus on Alzheimer's disease classification using 2D magnetic resonance imaging (MRI). Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP) are employed to extract discriminative features from MRI images; however, due to the high dimensionality of the extracted features, dimensionality reduction is required. Principal Component Analysis (PCA) is utilized to reduce feature dimensionality while preserving most of the relevant information, as reflected in the improved performance of the underlying machine learning (ML) classifiers. Two feature extraction pipelines are evaluated: (i) HOG combined with PCA, and (ii) LBP combined with PCA. The reduced feature sets are subsequently used for classification. Experimental results demonstrate that ML algorithms consistently achieve superior performance using features derived from the HOG+PCA pipeline compared to those obtained from the LBP+PCA pipeline. Although the LBP+PCA approach exhibits certain advantages, HOG+PCA proves to be more effective for the problem under consideration, while acknowledging that performance may vary across applications. Furthermore, the study confirms that ensemble learning methods generally outperform individual classifiers by leveraging complementary strengths, and that larger datasets tend to enhance model performance by enabling the learning of richer patterns. In contrast, memory-intensive algorithms such as k-nearest neighbors (KNN) may be suitable for smaller datasets but are typically less scalable for large-scale applications.

Keywords: medical imaging, feature extraction, ensemble techniques, histogram of oriented gradients, local binary patterns, PCA.

1 Introduction

Histogram of Oriented Gradients (HOG) determines the pixel variation across the image to describe its

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structure and other related properties. HOG performs this task by partitioning the underlying image in sub-parts and then determines the direction of the change of brightness, which is ultimately translated into corresponding histograms. This process is then standardized for larger regions of the image to make it less vulnerable to variations in shadows or lighting conditions. Due to the proven capabilities of this technique in finding edges or outlines, it is extensively used in medical imaging or object identification [1–4]. In contrast to this, Local Binary Patterns (LBP) mainly relies upon the textures of the image [5]. It works by comparing the brightness of every pixel to its neighboring ones, based on which they are assigned binary codes as per the differences in their brightness values. These binary values are subsequently decoded into numbers that map to corresponding patterns of the texture which are represented in the form of Histograms. LBP finds its application in texture-based image-recognition due to its simple, quick and reliable functioning even under inconsistent lighting conditions. The features obtained from these techniques can then be implemented on different classifiers i.e., "Support Vector Machine (SVM)", "Random Forests (RF)", "K-Nearest Neighbors (k-NN)" [6] or these features can be fused with "Convolutional Neural Networks (CNN)" also [7]. As both HOG and LBP generate a considerable number of features from large images, this can negatively impact the performance of the underlying classification models in terms of speed and accuracy. This problem can be resolved using "Principal Component Analysis (PCA)", which brings down the number of features while still holding a significant amount of important information in the original feature-set [8]. These methods are used in practice for tasks like categorization and object identification. Even though CNN and other contemporary Deep Learning (DL) techniques rule this field, HOG and LBP continue to exhibit remarkably strong performance [9, 10]. For instance, combining HOG and LBP with multiclass SVM produced great results on the Fashion-MNIST dataset, which consists of millions of photos of apparel items. These results were comparable to CNN features paired with SVM [11].

This work highlights how the performance of Machine Learning (ML) algorithms can be enhanced by lowering feature dimensions. After converting the images into HOG or LBP features, they were reduced using PCA and then categorized using several methods. Particularly for complicated data like brain scans, the reduced input not only expedited the process but also improved the models' ability to generalize. To put it briefly, one of the most important steps in machine learning for image processing is feature extraction. A powerful and effective method of preparing data for classification is to combine HOG or LBP with PCA, showcasing that manual techniques may still be used in conjunction with DL in visual and medical applications.

1.1 Feature representation and compression

Techniques for lowering the quantity of input variables in a dataset are referred to as dimensionality or feature reduction. ML algorithms may overfit when a dataset has a large number of features but comparatively few examples, which lowers the algorithms' accuracy. Reducing features does not mean that crucial information is lost; rather, it helps get rid of unnecessary or redundant data, which frequently boosts productivity and model performance. Using fewer features also reduces processing needs, expedites training, and improves model generalization to new data. There are several popular methods for reducing dimensionality: (a) Feature selection is often applied to the underlying data so as to keep the highly relevant features and discard the redundant or unimportant ones. These methods are further categorized into filter and wrapper ones, while the former are based on statistical approaches, i.e., correlation or chi-square tests, etc., the latter use subset approach for selecting the most appropriate features from the original dataset. Feature selection improves the performance of the underlying classification algorithm by reducing the running time and also computational complexity of the system.

b) PCA is a type of feature or dimensionality reduction technique. It works by transforming the feature matrix into new dimensions using the concept of eigen vectors and eigen values [12]. The data that aligns with the principal components, provides the maximum variance for the classification purpose, thus, representing the most important features in the new dimensional space.

c) Autoencoder, a type of DL model, is also sometimes used for reducing the dimensions of the underlying dataset. These are basically a combination of encoders and decoders, the former part is used for compressing the data, whereas the later one rebuilds it. The output of the encoder can be utilized as a condensed feature set for categorization. In situations where standard approaches might not be able to handle high-dimensional input, such as photographs, autoencoders perform exceptionally well.

Generally, a large number of features means, more information from the underlying dataset. However, processing such a large amount of data requires more computational resources and time, thus, negatively impacting the performance of the underlying system. Therefore, reducing the dimension of the given dataset is essential, but utmost care must be taken while carrying out this task, so as to prevent the loss of important information from the underlying dataset. Simplifying the dataset and the model while preserving the essential details required for precise classification is the primary objective.

PCA involves a number of crucial steps:

1. Standardizing the data ensures that each feature contributes equally and eliminates biases brought on by scale variations.

2. Calculation of the covariance matrix: Finds redundancy by detecting correlations between features.

3. Eigenvalues and eigenvectors: Eigenvalues show the significance of eigenvectors, which establish new axes (principal components). Most of the information from the original data is retained in these new, uncorrelated components, which are arranged according to relevance.

4. Composition of feature vectors: This method creates a smaller feature space by choosing the most significant elements.

5. Recasting data: This process generates a smaller dataset that retains the most important information while eliminating extraneous dimensions by projecting the original dataset onto the chosen components.

Classifiers operate more quickly, need less computing power, and may even perform better overall when PCA or related methods are used.

2 Literature Review

In many image classification tasks, the combination of HOG and LBP descriptors with classifiers such as SVM and CNN has yielded good results. Handcrafted techniques like HOG and LBP are helpful since they are straightforward, effective, and simple to understand, but CNNs have the benefit of automatically learning intricate features. Combining the two strategies into hybrid models that can capitalize on each other's advantages is a viable future roadmap [13, 14]. Research also demonstrates that no single method is optimal for all issues [15]. CNN features excel when there is an abundance of available data, LBP and GLCM perform well for texturing, DWT provides information at many scales, and HOG is good at capturing forms and edges. Combining complementary techniques frequently yields the finest outcomes. The dataset, the task at hand, and the available computing power all influence the best option [16–20]. While one concentrates on textures and the other on shape details, still, HOG and LBP complement each other effectively. However, because both produce very large feature sets, dimensionality reduction is frequently required to improve processing efficiency. Together, they offer more comprehensive data, enhancing classification tasks' accuracy and resilience [1, 21]. Combining these descriptors improves the way forms and textures are represented, resulting in improved classification even when there are structural or illumination changes [22]. They provide a well-rounded and efficient answer to difficult image analysis issues when combined. Scalability will be an increasingly significant issue as datasets continue to grow. Methods like T-distributed Stochastic Neighbor Embedding (t-SNE) or PCA can assist in lightening the load while preserving the most crucial data. DL combined with handcrafted descriptors may eventually result in more versatile systems that perform well on both tiny medical datasets and large-scale computer vision issues.

3 Methodology

3.1 Using reduced HOG feature set for classification in experiment 1

This experiment aims to investigate how well feature extraction methods perform when dimensionality reduction is used. This study included two tests, each of which focused on a distinct feature extraction technique. Moreover, it utilized 2D MRI dataset, which was prepared from baseline MRI (NIFTI) dataset accessed from ADNI after careful extraction of the constituent slices from the MRI images. This 2D dataset is prepared from the ADNI Baseline dataset containing 199 MRI instances. Multiple slices were extracted from a single MRI scan using python code. This was followed by selection of those 2D slices, which contained significant information about the brain through visual inspection. The resulting dataset consisted of a total of 5154 2D MRI slices, comprising 1124 "Alzheimer's (AD)" images, 2590 are of "Mild

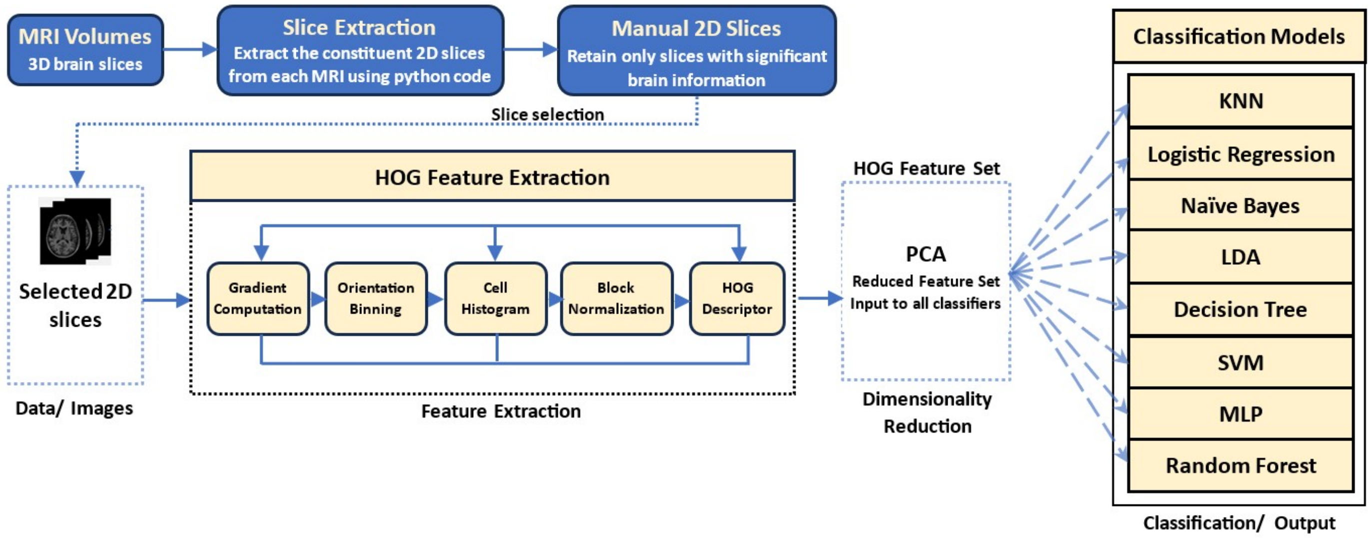

Figure 1. Evaluation of different classifiers on reduced HOG feature set.

Cognitive Impaired (MCI)", and 1440 are that of "Cognitive Normal (CN)". The first experiment of this study is based on HOG. It is a popular feature extractor, which is generally used for classification-based tasks, and it has shown good performance in such tasks. This section covers the implementation of HOG for extracting features from the underlying 2D MRI slices which are first treated with PCA so as to reduce their dimensionality. The resulting feature-set is then fed to the ML algorithms. These ML algorithms then classify the underlying images to their corresponding classes based on their learning from the given feature set of the said images. Stepwise process of the experiment is discussed below:

(1) Feature extraction: HOG was implemented on the given 2D MRI slice dataset which produced a feature-set consisting of 3,780 features. As already discussed, this step is carried out so as to reduce the computational burden and the training time for the given traditional ML algorithms.

(2) Dimensionality reduction: The features obtained in the previous steps are then passed through PCA so as to bring down the dimensionality of the data. This again is done to retain only important features while discarding the non-essential or redundant information from the feature-set obtained in the previous step.

(3) Selection of principal components: PCA produced 200 principal components, which captured almost 98.9% of the variance in the original dataset and ensured that the majority of the important information was retained.

In order to create a new, compact feature vector that could be used as the input for the classifiers, these principal components were concatenated. The ML algorithms were then fed this condensed feature vector in order to assess how well they performed on a more manageable but still relevant dataset. The stages used in this experiment are depicted in Figure 1, which also displays the entire workflow.

It is crucial to consider the input image size while applying the HOG feature extraction approach. For optimal results, the width and height should ideally be in a 1:2 ratio. HOG's ability to compute gradient directions and magnitudes locally is one of its main advantages. This enables it to detect minute details and extract the image's most pertinent aspects. HOG is good at catching minor structural patterns because it is sensitive to even slight changes in orientation.

HOG collects data at the local, pixel level and combines histograms into larger blocks to achieve global pooling. This allows it to capture both fine-grained details and broad patterns, resulting in a comprehensive and well-rounded feature collection. Table 1 presents the findings from the application of classification methods to these HOG features. AUC, F1-score, recall, accuracy, precision, and other metrics are used in the experiment to assess performance and provide a clear overview of the classifiers' performance with these features.

The visual representation of the results is provided in Figures 2, 3, 4, 5, and 6.

3.2 Using reduced LBP Feature set to assess classifier performance in Experiment 2

The reduced HOG feature set was used to evaluate the performance of different ML methods in experiment

Table 1. Evaluation of classifier performance with reduced HOG features.

Classifiers	Training Accuracy	Test Accuracy	Recall	Precision	F1-Score	AUC
SVM	99.92	99.92	100	100	1	1.000
Logistic Reg.	97.31	94.34	94	94	0.94	0.992
LDA	91.93	90.15	89	90	0.9	0.982
MLP	100.00	99.46	99	99	0.99	1.000
Decision Tree	97.67	89.91	85	86	0.85	0.931
Naïve Bayes	89.91	87.98	87	88	0.87	0.969
KNN	99.97	99.92	100	100	1	1.000
RF	100.00	99.15	99	99	0.99	1.000

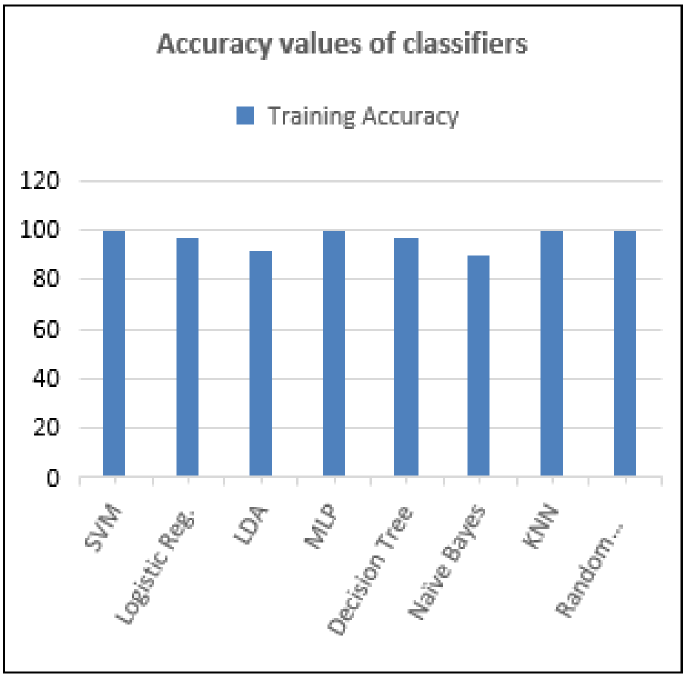

Figure 2. Accuracy values of classifiers for reduced HOG features.

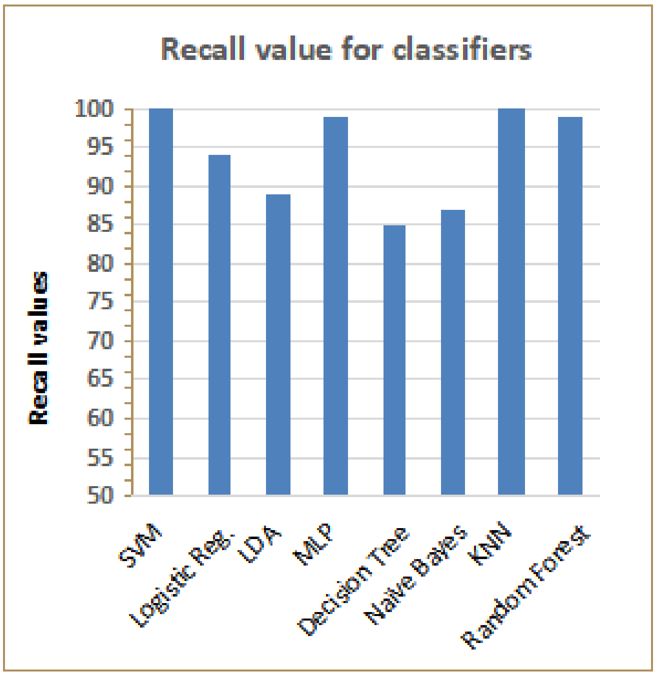

Figure 3. Recall values of classifiers based on reduced HOG features.

1. In this experiment, the performance of the same classifiers on a reduced LBP feature set is examined, expanding on that investigation as in the last experiment, the dataset and classification algorithms are unchanged. Like HOG, the choice of LBP was made in light of the literature review's conclusions, which emphasize LBP's aptitude for capturing texture-based photo characteristics.

Global feature representations are created by LBP by combining local descriptors that are extracted from the images. PCA is then used on these features in order to reduce their dimensionality and make them easier for traditional ML techniques to handle.

The following is a summary of the experimental process:

1. Feature Extraction: The LBP algorithm employed NumPy arrays to represent the 2D pictures, yielding 16,384 features per image. Standard classifiers may find it difficult to directly handle such a high-dimensional feature set.

2. Dimensionality Reduction: PCA was used to process the high-dimensional LBP features in order to decrease the number of features.

3. Principal Component Selection: PCA conserved almost all of the significant information from the original features by reducing the feature set to 200 principal components, which kept 98.9% of the original variance.

4. Creation of Reduced Feature Set: These 200 principal components made up the new, reduced feature vectors, which were then employed in the testing and training of classifiers.

The performance of the classifiers was then assessed

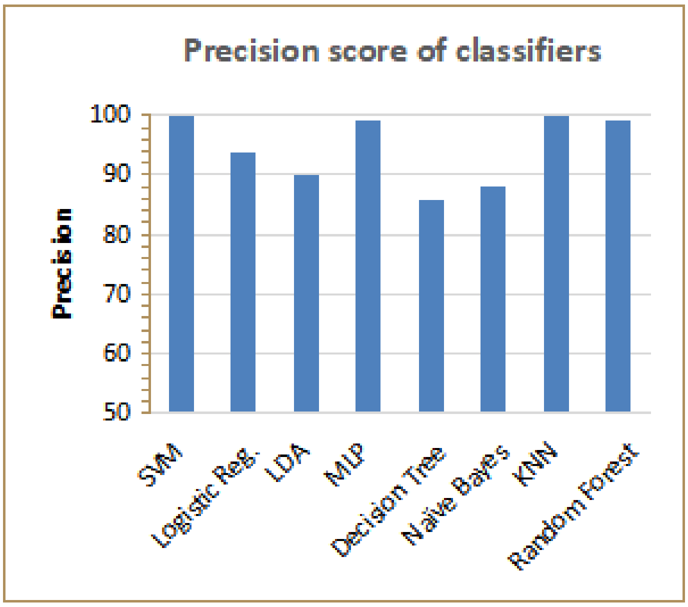

Figure 4. Evaluation of classifiers in terms of precision on reduced HOG features.

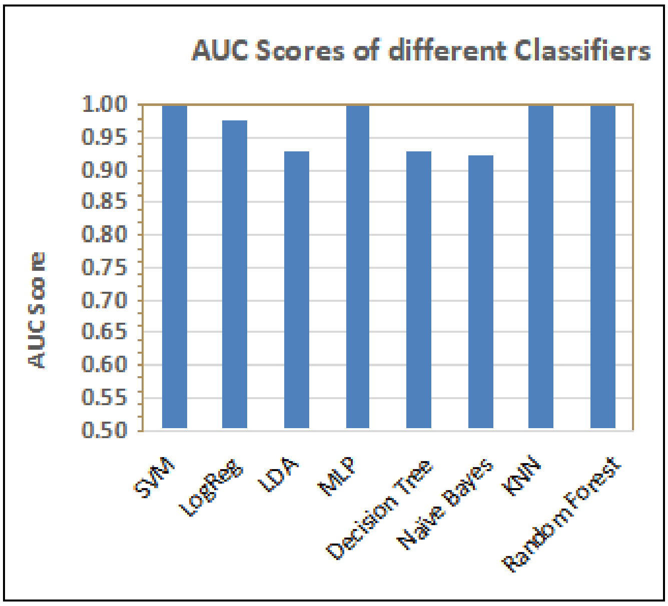

Figure 6. AUC performance of classifiers using reduced HOG features.

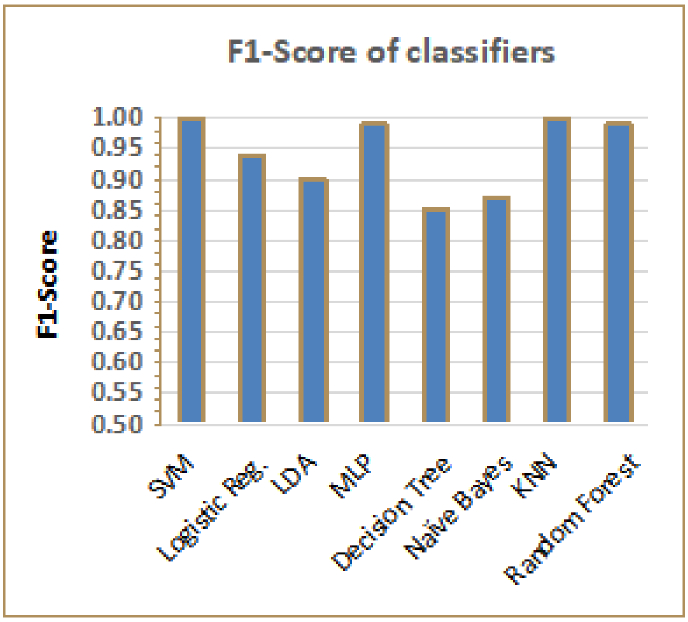

Figure 5. Evaluation of classification algorithms based on F1-score with reduced HOG features.

using the reduced LBP features, and the outcomes were noted. Figure 7 shows the entire process, from extracting LBP features to evaluating the classifier. This setup showcases how well LBP and PCA work together to reduce feature dimensionality while preserving important information, enabling a straightforward evaluation of classifier performance on the feature set that has been modified.

For classification problems, the combination of LBP and PCA works well. The outcomes from the dataset utilized in this experiment show that it performs well, especially on monochrome grayscale inputs. An overview of the reported results is shown in Table 2. When used with PCA, LBP offers a powerful method for resolving classification issues. Experimental results show that it is robust on monochrome grayscale images. For classification problems, combining LBP with PCA provides a successful approach that consistently performs well on monotonic grayscale inputs. Table 2 provides a summary of the experiment's results.

SVM: Support Vector Machine, Logistic Reg.: Logistic Regression, LDA: Linear Discriminant Analysis, MLP: Multi-Layer Perceptron, KNN: K-Nearest Neighbor, RF: Random Forest

Likewise, the performance of the classifiers on the chosen evaluation parameters is depicted in Figures 8, 9, 10, 11, and12.

Important conclusions from the analysis of the Experimental findings are further explained in the next section.

4 Observations and Calculations

ML and DL techniques are becoming popular for solving real-life problems [23, 24]. However, their performance is improved by using feature extraction or reduction techniques on the underlying data. From the current study, several important observations and inferences can be made considering the experiment's results:

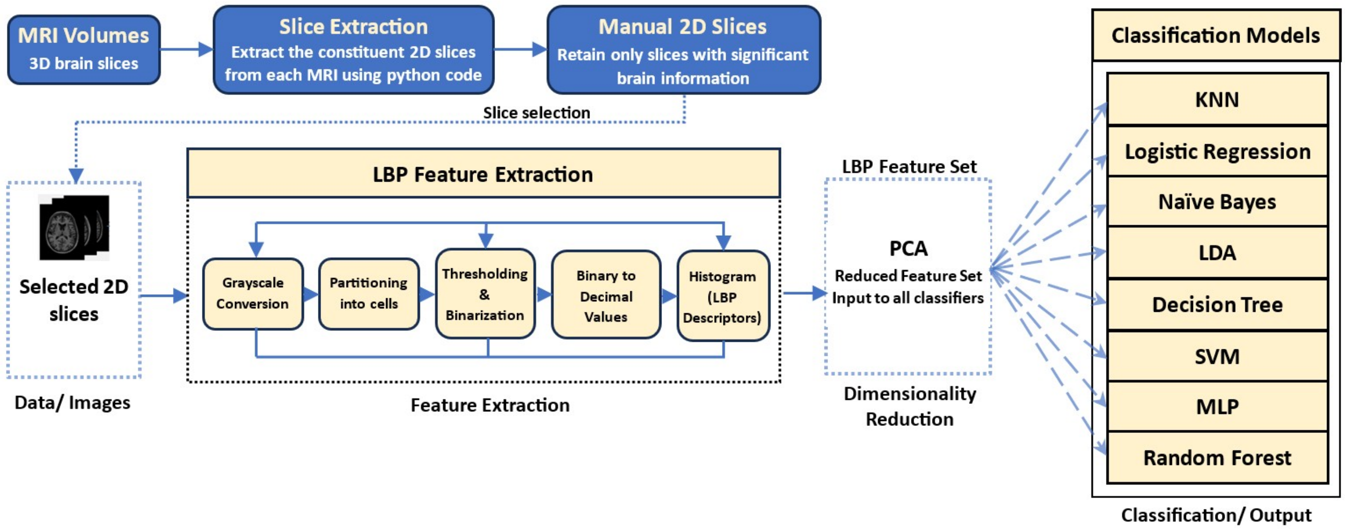

Figure 7. ML based classification of reduced LBP feature-set.

Table 2. Performance comparison of different classifiers using the reduced LBP feature set.

Classifiers	Training Accuracy	Test Accuracy	Recall	Precision	F1-Score	AUC
SVM	99.59	98.60	98	99	0.99	1.000
Logistic Reg.	94.05	91.16	90	92	0.91	0.982
LDA	89.44	87.35	86	88	0.87	0.964
MLP	100.00	99.22	99	99	0.99	1.000
Decision Tree	99.61	94.18	94	94	0.94	0.958
Naïve Bayes	85.38	82.62	84	83	0.83	0.953
KNN	100.00	100.00	100	100	1.00	1.000
RF	100.00	98.76	98	99	0.99	1.000

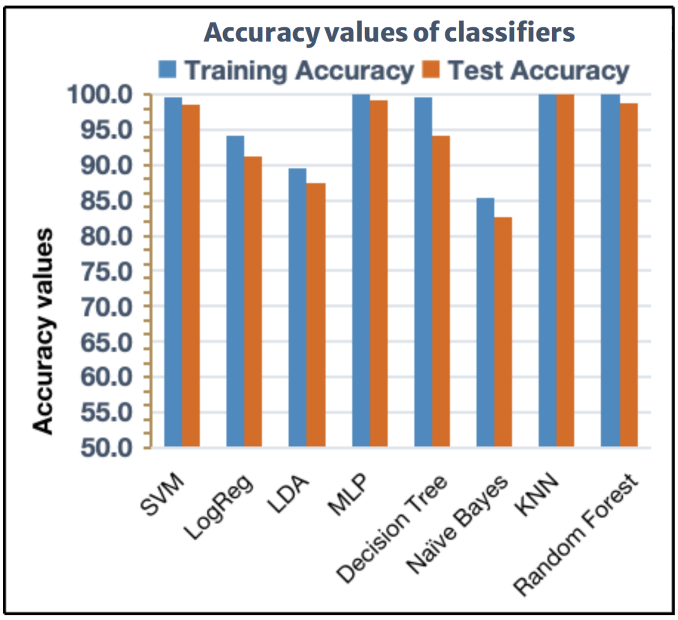

Figure 8. Classification accuracy scores on reduced LBP features for different algorithms.

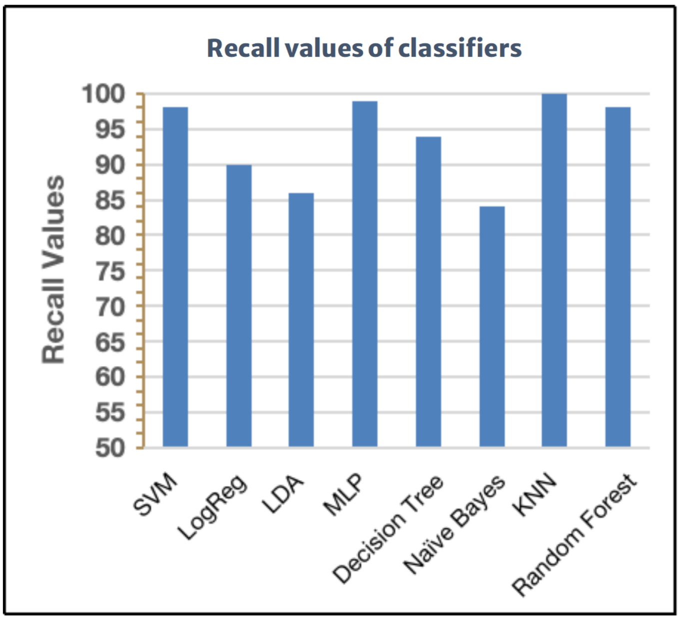

Figure 9. Comparison of recall values for classifiers applied to the reduced LBP feature set.

4.1 Findings from HOG + PCA

I. HOG and PCA together routinely perform better than PCA alone. This is probably because HOG actively extracts pertinent and discriminative features from the images, whereas PCA mainly reduces dimensionality. The approach improves overall

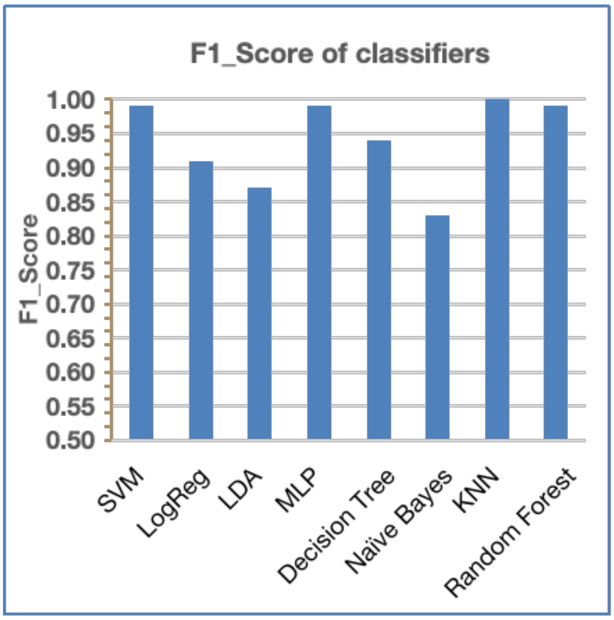

Figure 10. Evaluation of classifiers based on F1-scores on the reduced LBP feature set.

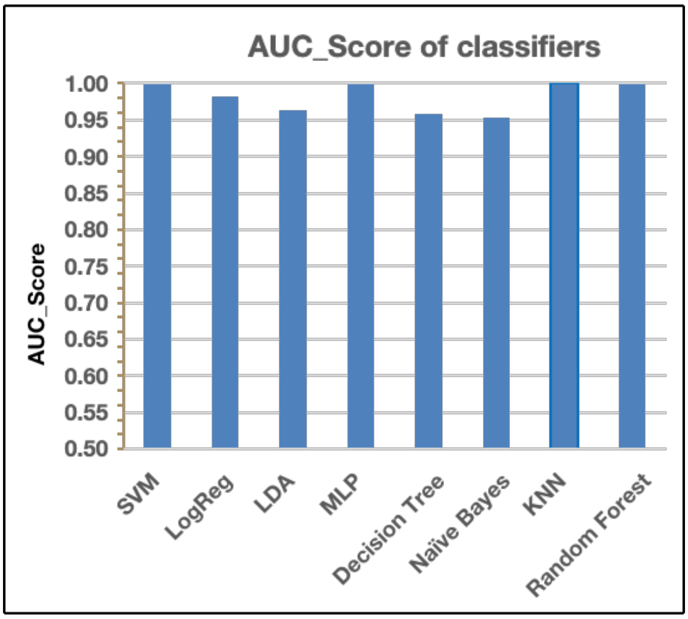

Figure 12. AUC values of the given classifiers applied on the reduced LBP feature sets.

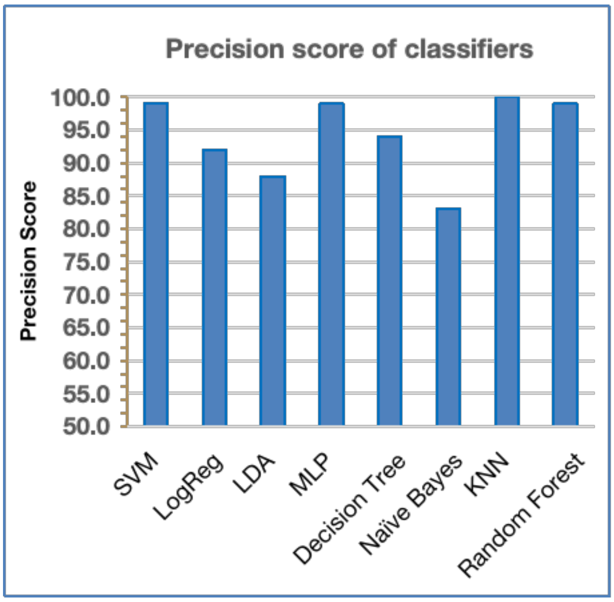

Figure 11. Classifier Precision values evaluated on the reduced LBP feature set.

performance as well as class-specific predictions, as evidenced by the consistent performance improvement across all metrics, including accuracy, F1-score, precision, recall, and AUC. Faster classifier training and testing are made possible by the huge reduction in computational complexity, both in terms of time and memory, that results from creating features with HOG and reducing them with PCA.

II. The overall findings show that HOG is a dependable and efficient feature extractor, particularly for applications involving medical imaging.

III. The finding that classifier effectiveness frequently increases with more data is supported by additional patterns, such as the enhanced performance of ensemble approaches, SVM, and MLP on larger datasets. For applications like brain image analysis, where minute fluctuations have diagnostic importance, HOG features are essential because they are resilient to changes in picture intensity and direction.

4.2 Findings from LBP + PCA

I. Although it is marginally less successful than HOG + PCA, the LBP and PCA combination also enhances classifier performance when compared to PCA alone.

II. Despite having slightly lower performance than HOG, LBP is quite useful for feature extraction tasks, this is due to the fact that it is able to collect both structural and textural outlines in images. Generally, it is expected to perform better on those types of images, where textural patterns give greater information as compared to that of gradient-based features.

III. As the performance of the given algorithm primarily depends upon the problem (data) at hand, so it is quite possible that in some cases, LBP + PCA may outperform HOG + PCA combination.

4.3 Overall Conclusions across Experiments

a) Feature extraction techniques are generally used to extract meaningful and important information from the raw images, HOG and LBP are one of the few examples of such kind of techniques. Moreover, the features can be quite large in number, which may impact the performance of the underlying classifiers, thus, PCA comes into the picture, which is a dimensionality reduction technique. Such algorithms make the feature-set compact, thereby reducing the computational burden on the classifiers while preserving meaningful information within the underlying feature-set.

b) HOG and LBP both show how crucial it is to combine feature extraction and dimensionality reduction to strike a balance between computational efficiency and information retention.

c) More complicated patterns and correlations between input features and target variables can be detected by algorithms due to larger datasets, which improve classifier performance. In general, ensemble methods (like RFs) perform better than individual classifiers since they aggregate weak learners; yet certain situations may call for algorithms like SVM or MLP.

d) Because it stores the complete dataset, KNN is good at what it does but is less appropriate for big datasets. Both the quality of feature extraction and the dimensionality reduction technique have a significant impact on classifier performance.

e) Feature engineering done right can significantly increase prediction accuracy. These tests show that a practical and effective framework for medical image classification, especially in Alzheimer's diagnosis, can be achieved by combining robust feature extraction (HOG or LBP) with effective dimensionality reduction (PCA).

5 Conclusion

The experimental findings show that the effectiveness of conventional ML classifiers in medical image analysis is significantly improved when feature extraction and dimensionality reduction are combined. Both HOG and LBP are good feature extractors, but still the resulting features cannot be used directly due to the computational load on the underlying system. Thus, their dimension needs to be reduced, which is done using PCA, which not only reduces the dimension of the resulting data but also minimizes the redundancy in it without compromising the important information. It is also observed that HOG captures deeper structural and discriminative information. This when combined with PCA produces better results than those obtained after implementing PCA alone on the given dataset. The combination of LBP with PCA also produces similar results, but slightly low performance as compared to that of HOG+PCA combination. However, this is not always the case as the performance of the feature extraction and ML algorithms is generally domain-specific. Larger datasets significantly improve classifier performance, according to the study, with ensemble approaches, SVM, and MLP demonstrating high flexibility. On the other hand, KNN's high memory requirements make it difficult to scale, even when it achieves good accuracy. These results demonstrate that well-chosen feature extraction and reduction technique combinations not only increase accuracy but also boost the effectiveness and usefulness of models for actual medical imaging applications. In conclusion, the findings highlight how algorithm performance is heavily influenced by the particular issue domain and confirm the usefulness of conventional ML techniques, which are backed by HOG, LBP, and PCA, as reliable baselines for diagnostic tasks.

The current work can be extended in the future so as to combine multiple DL techniques for both extraction and classification purposes. Moreover, datasets from other online repositories and even primary data can be utilized for making generalized diagnostic models for a given disease. A complete system can be made, including user interface with the generalized model integrated into it, to assist the practitioners in diagnosing a given disease.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

Ethical Approval and Consent to Participate

This study used anonymized data from the ADNI database. The original ADNI study was approved by the IRBs of all participating institutions, with informed consent from participants. No additional ethical approval was required for this secondary analysis.

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