International Journal of Innovative Research and Scientific Studies, 8(2) 2025, pages: 696-703

ISSN: 2617-6548

URL: www.ijirss.com

A comparative analysis of HOG and LBP feature extraction techniques in AdaBoost for image recognition

Aziz Ilyas Ozturk[1*], Osman Yildirim[2]

[1]*General Electric Healthcare, Istanbul, Turkey.*
[2]*Istanbul Aydin University, Faculty of Engineering, Department of Electrical and Electronics Engineering, Istanbul, Turkey.*

Corresponding author: Aziz Ilyas Ozturk (*Email: aziz.ozturk@gehealthcare.com*)

Abstract

Arachnoid cysts are cerebrospinal fluid-filled sacs located between the brain or spinal cord and the arachnoid membrane. Detection of these cysts is critical for early diagnosis and treatment planning. In this study, deep learning algorithms were developed and applied to improve the detection of arachnoid cysts in brain MRI scans. Two separate feature extraction methods, namely Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG), combined with the AdaBoost classifier, were tested. The results showed that the AdaBoost classifier with LBP achieved an accuracy of 0.77, while the AdaBoost classifier with HOG performed significantly better with an accuracy of 0.95. These findings suggest that HOG features are more effective in distinguishing arachnoid cysts from normal brain tissue. This study contributes to the growing body of research on automatic brain anomaly detection and highlights the potential for improving diagnostic accuracy using advanced machine learning techniques.

Keywords: AdaBoost, Arachnoid cyst, Histogram of oriented gradients, Local binary patterns.

DOI: 10.53894/ijirss.v8i2.5290
Funding: This study received no specific financial support.
History: Received: 27 January 2025 / **Revised:** 28 February 2025 / **Accepted:** 6 March 2025 / **Published:** 11 March 2025

Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.
Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Publisher: Innovative Research Publishing

1. Introduction

AdaBoost is one of the most popular and effective ensemble methods and is known for its ability to combine weak classifiers to form a strong classifier. First proposed by Freund and Schapire, AdaBoost plays an important role in machine learning, especially in dealing with imbalanced datasets. This algorithm evaluates the misclassified examples with higher weights during the learning process, thus allowing more focus on these examples. This approach provides a suitable solution for difficult problems such as imbalanced datasets [1].

Imbalanced datasets refer to situations where one class has a much smaller number of instances than the other class, and this poses a major challenge for learning algorithms. AdaBoost has emerged as a successful method for dealing with imbalanced datasets because it repeatedly builds weak classifiers to better learn minority classes and gives more weight to misclassified instances at each stage. Consequently, it yields more accurate results for classes with fewer instances [2, 3].

Two basic feature extraction methods widely used in image processing and computer vision are Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP). HOG has achieved significant success in object recognition and classification problems by capturing edge orientations and local shape information in an image. HOG calculates edge orientation histograms for each image region, representing the structural features of the objects in the image. HOG has proven to be particularly effective in applications requiring high accuracy, such as human detection [4, 5]. HOG's primary benefit lies in its ability to extract orientation information, enabling object recognition regardless of varying lighting and perspective angles.

On the other hand, Local Binary Patterns (LBP) is a simple but effective method for analyzing texture and local patterns in an image. LBP transforms the local texture into a numerical form by converting the relationship between each pixel and its neighbors into binary values. It has shown successful results, especially in applications such as face recognition, texture analysis, and biometric identification. The main advantages of LBP are its low computational cost and its robustness to various lighting conditions [6, 7]. However, since LBP is based only on the interactions of local pixels, it may have limitations in identifying more complex and large-scale patterns. Deep learning-based approaches often integrate these two methods in computer vision applications to enhance feature extraction.

In this study, the AdaBoost algorithm is used to detect arachnoid cysts in brain images and is tested with two different feature extraction methods: Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG). AdaBoost was successful with both feature extraction methods, but the accuracy was higher with HOG. This success shows that AdaBoost is a powerful method in feature extraction and classification and has potential in biomedical image analysis.

2. AdaBoost

AdaBoost (Adaptive Boosting) is an ensemble algorithm developed to improve the performance of weak classifiers in machine learning. Weak classifiers are simple models whose performance is slightly better than random guessing, and the aim of the algorithm is to build a strong classifier by progressively correcting the errors of these classifiers. In this process, the misclassified instances become more salient in the later steps of the algorithm, and thanks to this adaptive structure, the contribution of each weak classifier is dynamically adjusted according to the data. The algorithm works by training the weak classifiers one after the other; at each iteration, the current data is analyzed, and a new weak classifier is created by giving more weight to the misclassified examples. This method aims to reduce the error rate by focusing on the misclassified instances, and in the final stage, all weak classifiers are combined together to form a final strong classifier [8, 9].

The advantages of Adaboost include simplicity and flexibility, resistance to overfitting, theoretically sound construction, and dynamic weighting. The algorithm is easy to implement and can work with different types of weak classifiers, often yielding good results with default settings without parameterization. Even when the number of iterations increases for large data sets, the algorithm is unlikely to overfit, as it improves the margins to extend the decision boundaries and reduce errors. It is based on a mathematically proven theory and can achieve strong results even when weak classifiers perform slightly above their errors. By focusing more on misclassified instances, it enables better learning of these instances and thus builds a stronger classifier.

However, the algorithm also has some limitations. Its sensitivity may be high in noisy data sets; incorrect labels or noise in the data may cause incorrect results, and if the weights of the mislabeled data increase, the model may try to adapt to such incorrect data and negatively affect performance. Furthermore, the computational cost may be high for large datasets, as weak classifiers need to be trained repeatedly. In order to improve the performance of the algorithm, hyperparameters such as the number of iterations may need to be set correctly, and these settings may vary depending on the dataset.

Adaboost can be successfully used in a wide range of applications such as computer vision, natural language processing, medical diagnostics, and finance. It is widely favored in computer vision tasks such as object detection, face recognition, and motion tracking, and is especially effectively implemented in the Viola-Jones face recognition algorithm. In natural language processing applications, it can be successfully used in tasks such as text classification, sentiment analysis, and language modeling. It can also be preferred in medical fields such as analyzing medical data and diagnosing diseases, as well as in finance and economics fields such as credit risk assessment, stock price prediction, and financial modeling to improve prediction performance [10-13]. In general, Adaboost is an efficient and flexible algorithm that builds a strong classifier using weak classifiers and has an important place in the fields of machine learning and deep learning due to its wide range of applications. Its advantages include high accuracy rates and resistance to overfitting, while its limitations include sensitivity to noisy data sets and high computational costs.

3. Histogram of Oriented Gradients

Histogram of Oriented Gradients (HOG) is a powerful feature descriptor widely used in image processing and computer vision, especially in tasks such as object recognition and human detection. To characterize the local object appearance and shape of an image, the HOG algorithm analyzes the directions of changes in pixel intensities and constructs a feature vector using the distribution of these directions in local regions. By dividing the image into small regions, this method creates a histogram of the gradient directions in each region, which are then transformed into a combined feature vector. To determine the gradient directions, intensity changes in the x and y directions are usually calculated, and the magnitude and direction of these gradients are added to the histograms in the corresponding cells [4, 14, 15].

The HOG algorithm is robust to illumination changes and ghosting because it includes local contrast norming operations. This norming is performed by normalizing the blocks containing the histograms of the cells together, thus reducing the effects of illumination changes and resulting in a more consistent feature vector. These blocks are often overlapped, which allows greater flexibility with respect to both spatial and photometric transformations. When constructing the histogram of gradient directions, the directional information obtained at the pixel level is usually quantized by a certain number of directional bins. This number of bins is directly related to the sensitivity of the model; using a low number of bins can lead to a loss of information, while a high number of bins can lead to the inclusion of unnecessary detail.

One of the main reasons for HOG's success in object detection is its ability to effectively capture local shape information, such as edge structures or gradient directions. In applications such as human detection, HOG's ability to analyze the vertical and horizontal gradient components, in particular, allows for accurate identification of various parts and shapes of the human body [16]. Used extensively on a regularly sampled grid of images, HOG, when combined with classifiers such as linear support vector machines (SVM), can create highly accurate object detection systems.

HOG can also be optimized to meet challenges in various areas. For example, the correct selection of parameters such as cell size or bin count can significantly affect performance in different application scenarios. Optimizing these parameters ensures that the correct information is maintained and detection accuracy is increased. The HOG algorithm is based on modeling the properties of shape-based objects in a discriminative way, and this approach is often most effective when the discriminative properties of a given class of objects are consistent.

In conclusion, HOG's high accuracy rates, robustness to various illumination and geometric transformations, and ability to capture local shape information have made it a popular choice in object detection and computer vision applications. The algorithm has been widely used in tasks such as human detection, face recognition, and expression classification, and it can achieve successful results on different datasets.

4. Local Binary Patterns

Local Binary Patterns (LBP) are widely used in image processing and pattern recognition and provide effective results, especially in applications such as texture analysis and face recognition. The main purpose of LBP is to capture the local textural features of an image. For this purpose, the intensity values of neighboring pixels around each pixel in an image are compared with the intensity of the central pixel. If the value of the neighboring pixel is greater than or equal to the central pixel, it is assigned a value of 1; otherwise, it is assigned a value of 0. These binary results are combined in a certain order to generate an LBP value corresponding to the central pixel, and this process is repeated over the whole image. Finally, these LBP values representing each region of the image are combined into a histogram summarizing the local textural information.

LBP has become very popular due to its simplicity and low computational cost, and it has the advantage of being robust to illumination changes. The algorithm is notable for being invariant to grayscale variations, making it a stable feature descriptor even under different lighting conditions. The flexible nature of LBP allows it to be applied in different sizes and at various scales, enabling it to effectively analyze both small details and the overall texture structure [16-18]. By providing a detailed description of the texture in a specific region of the image, significant success has been achieved, especially in applications such as face recognition and texture classification.

Various variations of LBP have been developed, and versions that are more robust to cyclic changes and provide better classification success with fewer texture patterns have been introduced. One of these variants is the "uniform" LBP, which is invariant to cyclic variations and minimizes the loss of local textural information. This approach allows one to express the textural patterns commonly found in the image in a lower-dimensional and more detailed way. In addition, different methods have been proposed to overcome the limitations of LBP in representing non-cyclic or complex patterns.

LBP is used in a wide range of applications such as face recognition, text classification, and medical image analysis. In these areas, it is preferred, and successful results are obtained due to its low computational cost and extensible structure. However, it has some limitations, such as transform invariance and sensitivity to noise. Therefore, more advanced versions and derivatives of LBP have been developed to overcome these limitations and have been successfully used in more complex application scenarios.

5. Comparison of AdaBoost-HOG and AdaBoost-LBP

The AdaBoost algorithm was evaluated with both LBP (Local Binary Patterns) and HOG (Histogram of Oriented Gradients) feature extraction methods, and the results were significantly different. These differences reveal how the algorithms handle various aspects of the image data and their effects on classification performance. Based on the given results, both algorithms can be evaluated by comparing them extensively.

Firstly, while the accuracy rate obtained for the Adaboost_LBP algorithm was 77% (0.77), this rate was 95% (0.95) for the Adaboost_HOG algorithm. These results show that HOG features, when combined with the Adaboost classifier, provide a higher classification performance than LBP. A more detailed examination of the reasons underlying this difference will help to better understand the advantages and limitations of these two algorithms.

5.1. Representation of Features and Image Content

LBP is a method that represents the local textural features of the image. It creates a pattern by converting the intensity differences of each pixel in the image with respect to the surrounding pixels into binary values and extracts the histogram of these patterns. LBP performs particularly well in situations where textural information is important, such as texture analysis and face recognition. However, LBP's sensitivity to cyclic variations and its capture of lower spatial detail can lead to limitations, especially in the recognition of complex and finely detailed objects. In this instance, the system might have overlooked certain structural details during the distinction between cystless and cystic classes, leading to reduced performance in metrics like precision, recall, and F1-score. In particular, the recall value for the "With Cyst" class was as low as 48%, indicating that LBP was unable to recognize this class correctly.

HOG is a method that extracts edge information and shape-based features. It captures local shape information using histograms of gradient directions and their distributions in the image. HOG is particularly successful in applications such as object detection and human detection, where edge structures and directional information are important. In images with and without cysts, HOG's better capture of edge and shape information has made the discrimination of classes more precise. This led the Adaboost_HOG algorithm to achieve 95% accuracy and significantly higher values in classification metrics. The recall value for the cystic class was 95%, and the F1-score was 93%, indicating that HOG was able to recognize this class with high accuracy.

5.2. Comparison of Accuracy and Metrics

In the Adaboost_LBP algorithm, the F1-score for the Cystless class is 85%, while it is 59% for the Cyst class (see Table 1). This difference indicates that LBP cannot recognize the Cyst class correctly, resulting in significant misclassifications, especially in the data for this class. Conversely, in the HOG-based methods, the F1-score is 93% and above for both the Cystless and Cyst classes (see Table 2), indicating that HOG is more consistent and performs better.

Table 1.
Classification report for AdaBoost-LBP.

Class	Precision	Recall	F1-Score	Support
No Cyst	0.78	0.92	0.85	146
Cyst	0.76	0.48	0.59	73
Accuracy			0.78	219
Macro Avg	0.77	0.70	0.72	219
Weighted Avg	0.77	0.78	0.76	219

Table 2.
Classification report for AdaBoost-HOG.

Class	Precision	Recall	F1-Score	Support
No Cyst	0.97	0.96	0.97	146
Cyst	0.92	0.95	0.93	73
Accuracy			0.95	219
Macro Avg	0.95	0.95	0.95	219
Weighted Avg	0.95	0.95	0.95	219

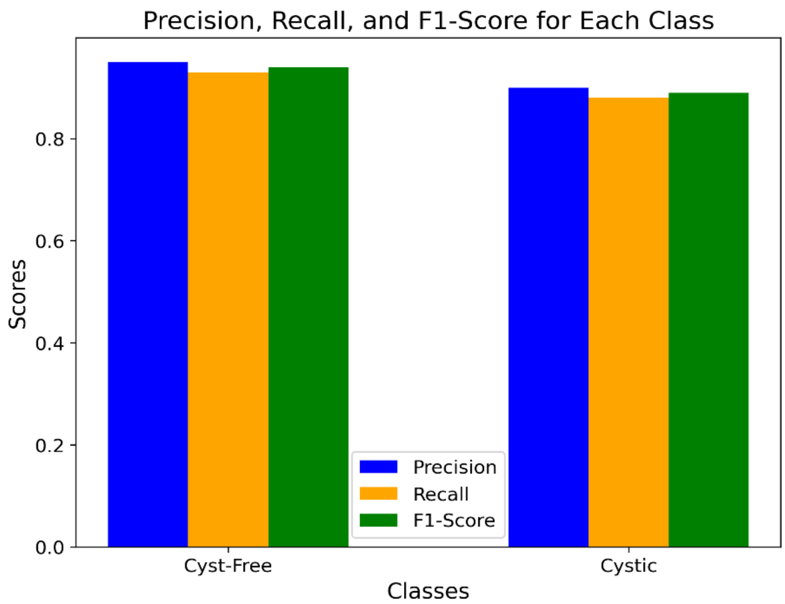

Figure 1.
Adaboost-LBP.

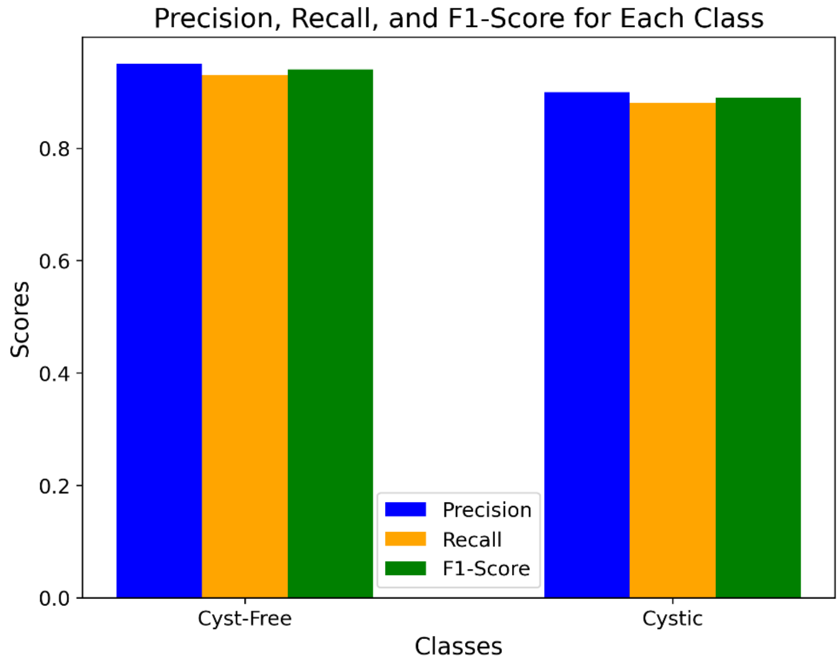

Figure 2.
AdaBoost-HOG.

Both algorithms aim to achieve effective results by combining the strong classification capability of AdaBoost with different feature extraction methods, namely HOG and LBP. A common observation in the results is the high accuracy on the training data, indicating that both algorithms successfully learn the data during the training process. However, their performance on the test data provides more insight into the algorithms' generalization capabilities. Dataset characteristics, problem nature, and algorithm hyperparameter settings can affect test accuracy.

HOG features, which better represent the shape and texture characteristics of objects, may lead to superior results in object recognition problems when using the AdaBoost_HOG algorithm. On the other hand, LBP features, which capture the local structural properties of faces more effectively, may make the AdaBoost_LBP algorithm more suitable for face recognition tasks. Therefore, when deciding which algorithm to use, careful consideration should be given to the nature of the problem being solved and the characteristics of the available dataset [19, 20].

Additionally, tuning the hyperparameters of both algorithms through experimentation with different values can significantly impact the model's performance. In particular, optimizing parameters such as the learning rate and the number of iterations is crucial for enhancing accuracy and generalization.

In conclusion, the AdaBoost_HOG and AdaBoost_LBP algorithms offer strong alternatives for image classification problems. However, which algorithm performs better may vary depending on the specific requirements of the problem and the characteristics of the dataset. Thus, comparing and experimenting with different algorithms to choose the most suitable one is essential for obtaining more accurate and reliable results. Figures 3 and 4 present the accuracy comparisons and train-test accuracy evaluations for both algorithms.

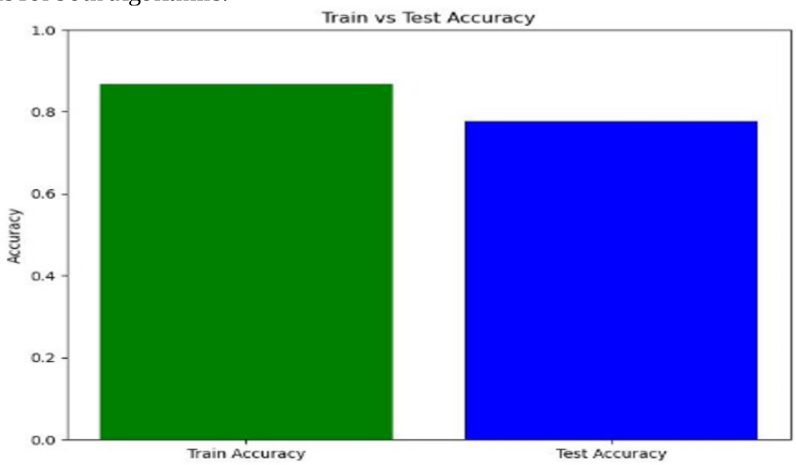

Figure 3.
Adaboost-LBP training-accuracy.

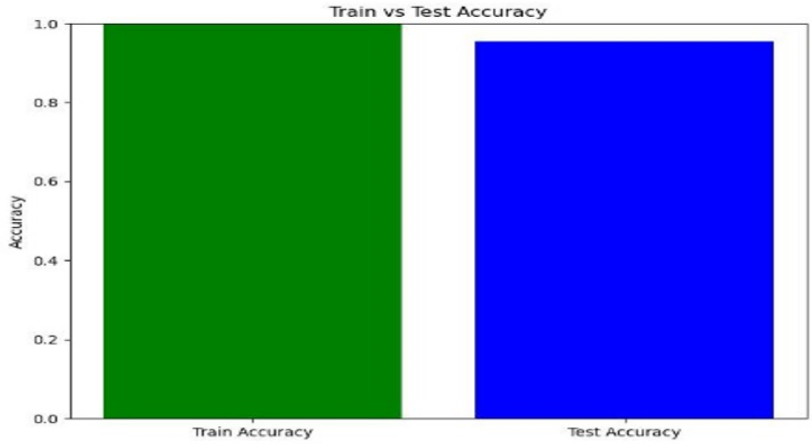

Figure 4.
AdaBoost-HOG training-accuracy.

5.3. Advantages and Limitations of Algorithms

An advantage of LBP is that it is simple and has a low computational cost; it can be computed quickly, and it can be used on large data sets. However, it is not sensitive to cyclic transformations and small-scale details when capturing textural information. This limitation may have resulted in an inability to accurately recognize the Cysted class.

The advantage of HOG is that it can effectively capture shape-based features and edge structures. This allows it to more accurately represent the distinctive edge structures of the Cyst and Non-Cyst classes. However, the computational cost of HOG may be higher, and the processing time may increase for more complex datasets. Nevertheless, according to the results in this study, the performance superiority of HOG justifies these costs.

5.4. Comparison with Supported Literature and Previous Studies

In the literature, it is known that HOG outperforms LBP in many areas such as human detection, object detection, and medical image analysis. This is because HOG can capture structural information in the image in greater detail. For example, it is frequently reported that HOG yields better results than LBP in studies such as face recognition and expression recognition. This study aligns with the findings in the literature and demonstrates that HOG is more successful, especially in the discrimination of cyst and non-cyst classes.

This comparison reveals that HOG features provide a stronger and more consistent classification performance. This is because HOG can extract features with more discriminative and structural information. This is why the Adaboost_HOG algorithm is better at accuracy and classification. Due to certain limitations of LBP, HOG yields more successful results. Therefore, HOG can significantly improve the classification performance in similar applications where accurate separation of cyst and non-cyst classes is required.

5.5. Effect of Data Distribution

In the dataset, the number of instances of the No Cyst class is higher than that of the Cyst class. Such unbalanced data distributions may affect the performance of classification algorithms. In the Adaboost_LBP results, the F1-score of the Cystless class (85%) is higher than that of the Cyst class (59%), indicating that LBP is more successful in recognizing the Cystless class and is affected by data imbalance. The HOG-based method, on the other hand, seems to have managed to mitigate the negative effects of data imbalance by showing a balanced performance in both classes (97% and 93% F1-score). This allows HOG to be less affected by data imbalance, especially by better capturing distinctive edge structures and shape information.

5.6. Dimensionality of Features and Knowledge Representation

The dimensionality of the features extracted by LBP and HOG is also different, and this can affect classification performance. HOG generally produces feature vectors with higher dimensionality and richer information, which allows for more informed classification decisions. LBP, on the other hand, produces lower-dimensional and simpler feature vectors, which may result in the loss of some complex structural information [21, 22]. The results of this study confirm that HOG is more successful in classification due to its richer knowledge representation.

5.7. Resistance to Light Changes and Noise

LBP is known to be more robust to light changes because it relies on local textural information. However, in this study, HOG outperformed LBP despite light and contrast differences, indicating that HOG can compensate for the effects of noise and light changes by effectively utilizing local edge information and gradient distributions. This demonstrates that HOG can provide consistent performance in a wider range of imaging conditions.

5.8. Comparison with Deep Learning

In recent years, deep learning methods have made significant progress in image classification and feature extraction. Compared to traditional methods such as HOG and LBP, deep learning-based approaches are more flexible and capable of automatic feature learning. In future studies, the hybrid use of these traditional methods with deep learning algorithms or the experimentation of purely deep learning-based models can further improve performance.

As a result, these additions make the comparison of the Adaboost_LBP and AdaBoost_HOG algorithms more comprehensive and evaluate the factors affecting classification performance in more detail.

6. Discussion

The AdaBoost classification algorithm was used to compare how well two different feature extraction methods, LBP and HOG, worked on medical images with and without cysts. The results show that the HOG-based model achieves a higher accuracy rate and superior values in classification metrics compared to LBP. The AdaBoost_HOG algorithm achieved 95% accuracy, while the AdaBoost_LBP algorithm achieved 77% accuracy. This difference reveals that the feature extraction methods used are one of the important factors determining classification success.

Simplicity and low computational cost, which are the main advantages of LBP, did not provide a decisive advantage in terms of classification performance in this study. LBP is a widely used method, especially in applications such as face recognition where textural information is at the forefront [23, 24]; however, in this study, it was limited in the discrimination of Cysted and Cystless classes. The difficulties experienced in the correct recognition of the Cyst class can be explained by the inability of this method to sufficiently distinguish structural details. In the classification report obtained, the F1-score value of the Cystic class for LBP remained at 59%, indicating that the method was insufficient in capturing the characteristics of this class.

The higher accuracy and consistency of the HOG-based model are due to its ability to extract features based on edge structures and gradient directions. The high performance of HOG in applications such as object detection and human detection has been frequently reported in the literature, and the findings of this study support this. The ability of HOG to produce high-dimensional feature vectors that carry more information in classification has enabled it to better identify the distinctive features of the Cyst and Non-Cyst classes. As a result, the HOG-based Adaboost model achieved an F1-score of 93% for the Cyst class, indicating that this method can perform more accurate and stable classifications.

7. Conclusion

This study shows that HOG offers superior classification performance compared to LBP due to its edge and shape-based information extraction capabilities. HOG-based approaches can be considered a more effective option in medical imaging applications where the distinction between cyst and non-cyst classes is critical. The combination of the proposed methods and the integration of more advanced algorithms can guide future studies to achieve more accurate and reliable results in medical image classification.

References

[1] Y. Freund and R. E. Schapire, "Experiments with a new boosting algorithm," *Machine Learning,* vol. 24, no. 2, pp. 149-171, 1996. https://doi.org/10.1023/A:1018054313458

[2] C. Seiffert, T. M. Khoshgoftaar, J. Van Hulse, and A. Napolitano, "RUSBoost: A hybrid approach to alleviating class imbalance," *IEEE Transactions on Systems, man, and Cybernetics-Part A: Systems and Humans,* vol. 40, no. 1, pp. 185-197, 2009. https://doi.org/10.1109/TSMCA.2009.2029559

[3] J. Zhu, H. Zou, S. Rosset, and T. Hastie, "Multi-class adaboost," *Statistics and Its Interface,* vol. 2, no. 3, pp. 349-360, 2009. https://doi.org/10.4310/SII.2009.v2.n3.a8

[4] N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," *IEEE Computer Society Conference on Computer Vision and Pattern Recognition,* vol. 1, pp. 886–893, 2005. https://doi.org/10.1109/CVPR.2005.177

[5] Q. Zhu, S. Avidan, T. Yeh, and K. T. Cheng, "Fast human detection using a cascade of histograms of oriented gradients," presented at the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2006.

[6] T. Ojala, M. Pietikainen, and T. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 24, no. 7, pp. 971-987, 2002. https://doi.org/10.1109/TPAMI.2002.1017623

[7] T. Ahonen, A. Hadid, and M. Pietikainen, "Face description with local binary patterns: Application to face recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 28, no. 12, pp. 2037-2041, 2006. https://doi.org/10.1109/TPAMI.2006.244

[8] Y. Freund and R. E. Schapire, "A decision-theoretic generalization of on-line learning and an application to boosting," *Journal of Computer and System Sciences,* vol. 55, no. 1, pp. 119-139, 1997. https://doi.org/10.1006/jcss.1997.1504

[9] Y. Ding, H. Zhu, R. Chen, and R. Li, "An efficient AdaBoost algorithm with the multiple thresholds classification," *Applied Sciences,* vol. 12, no. 12, p. 5872, 2022. https://doi.org/10.3390/app12125872

[10] P. Viola and M. J. Jones, "Robust real-time face detection," *International Journal of Computer Vision,* vol. 57, pp. 137-154, 2004. https://doi.org/10.1023/B:VISI.0000013087.49260.fb

[11] Q. Wu and P. Zhang, "Adaboost-based sentiment analysis for stock market prediction," *Journal of Computational Finance,* vol. 25, no. 3, pp. 67-82, 2021. https://doi.org/10.1016/j.jocf.2021.03.005

[12] R. E. Schapire and Y. Freund, *Boosting: Foundations and algorithms*. Cambridge Cambridge University Press. https://doi.org/10.1017/CBO9781139085905, 2013.

[13] L. Wang, Y. Deng, and Y. Du, "An improved AdaBoost algorithm for medical diagnosis," *IEEE Access,* vol. 7, pp. 76490–76499, 2019. https://doi.org/10.1109/ACCESS.2019.2921219

[14] Q. Dai, J. Zhao, C. Yang, and Q. Zhang, "HOG feature extraction from bayer pattern images," *IEEE Transactions on Circuits and Systems II: Express Briefs,* vol. 67, no. 5, pp. 946 - 950, 2020. https://doi.org/10.1109/TCSII.2020.2980557

[15] P. F. Felzenszwalb, R. B. Girshick, D. McAllester, and D. Ramanan, "Object detection with discriminatively trained part-based models," *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 995 - 1008, no. 5, pp. 995 - 1008, 2010. https://doi.org/10.1109/TPAMI.2010.167

[16] F. Bianconi, R. Bello-Cerezo, and P. Napoletano, "Improved opponent color local binary patterns: an effective local image descriptor for color texture classification," *Journal of Electronic Imaging,* vol. 27, no. 1, p. 011002, 2018. https://doi.org/10.1117/1.JEI.27.1.011002.

[17] U. Ojha and A. V. Sakhare, "Image processing techniques for object tracking in video surveillance—A survey," presented at the IEEE International Conference on Pervasive Computing, 2015.

[18] Z. Guo, L. Zhang, and D. Zhang, "A completed modeling of local binary pattern operator for texture classification," *IEEE Transactions on Image Processing,* vol. 19, no. 6, pp. 1657-1663, 2010. https://doi.org/10.1109/TIP.2010.2044957

[19] M. Ebrahimi and A. Barati, "A new approach for face recognition based on hybrid feature extraction and classification methods," *Journal of Ambient Intelligence and Humanized Computing,* vol. 12, no. 3, pp. 3409-3422, 2021. https://doi.org/10.1007/s12652-020-02702-0

[20] H. Mohammadi and M. Gholamzadeh, "A face recognition system based on LBP and Adaboost algorithm," *Journal of Soft Computing and Applications,* vol. 2017, pp. 1-10, 2017. https://doi.org/10.1155/2017/5906274

[21] G. Guo, L. Zhang, and Z. Li, "A study of texture features based on local binary patterns and HOG for improved classification performance," *Journal of Electronic Imaging,* vol. 28, no. 6, p. 061502, 2019. https://doi.org/10.1117/1.JEI.28.6.061502

[22] A. S. Kamarulzaman and M. R. Shahril, "Comparative analysis of LBP and HOG feature extraction methods for image classification," *Visual Computing for Industry, Biomedicine, and Art,* vol. 4, no. 1, pp. 1-12, 2021. https://doi.org/10.1186/s42492-021-00057-6

[23] M. K. Dhal and R. Krishnan, "Face recognition based on LBP and different distance metrics: A performance analysis," *International Journal of Computer Applications,* vol. 975, p. 8887, 2020. https://doi.org/10.5120/ijca2020920201

[24] D. C. Cireşan, U. Meier, and J. Schmidhuber, "Multi-column deep neural networks for image classification," in *Proceedings of the 2012 IEEE Conference on Computer Vision and Pattern Recognition,* 2011, pp. 3642-3649, doi: https://doi.org/10.1109/CVPR.2012.6248010.