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Eye Disease Classification Using K-Means Clustering Algorithm and Ensemble Classification Approach

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Abstract

In this study, we present a comprehensive approach for the classification of eye diseases, specifically targeting normal, cataract, glaucoma, and diabetic retinopathy conditions. This research uses a dataset from Kaggle, which provides a wide and varied collection of retinal images to ensure good representation. The methodology encompasses advanced image processing and machine learning techniques to ensure accurate diagnosis and prediction. The preprocessing phase involves a series of image enhancement techniques to improve the quality and features of retinal images. These techniques include histogram equalization, conversion to grayscale (rgb2gray), discrete wavelet transform (DWT), Haar wavelet transform, and Gaussian filtering. These steps are essential to highlight the relevant features and reduce noise, thereby facilitating better segmentation and classification. For the segmentation phase, we employ the k-means clustering algorithm combined with a Gaussian blur. This method successfully groups the retinal images into useful clusters, making it easier to extract important features and accurately pinpoint the areas of interest. During the classification stage, we use several machine learning models, such as decision tree, random forest, support vector machine (SVM), naïve bayes, boosted trees, and an ensemble classifier. Each classifier is thoroughly trained and tested using k-fold cross-validation, which helps ensure reliable performance results like accuracy, sensitivity, and specificity. To further enhance the performance and reliability of the classification system, we incorporate the synthetic minority over-sampling technique (SMOTE) to balance the dataset and address class imbalances. This step helps train the classifiers on a more balanced and representative dataset, which enhances their ability to make accurate predictions. The final prediction is obtained through an ensemble voting mechanism, where the individual predictions of all classifiers are combined to determine the most probable class for each test image. This majority voting approach leverages the strengths of each classifier, resulting in a more accurate and reliable diagnosis. Experimental results after hyperparameter tuning demonstrate that the proposed system achieves exceptionally high accuracy, sensitivity, and specificity in classifying normal, cataract, glaucoma, and diabetic retinopathy conditions, making it a valuable tool for automated eye disease diagnosis.

Keywords: Eye disease classification, k-means clustering, image segmentation, machine learning, ensemble voting, decision tree, SVM, random forest, naïve bayes, boosted trees, SMOTE, retinal image analysis, Kaggle dataset

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INTRODUCTION

In recent years, the application of machine learning techniques in medical image analysis has gained significant traction, particularly in the automated detection of eye diseases, such as cataract, diabetic retinopathy, glaucoma, and other conditions. Detecting these diseases early and accurately is essential to prevent serious vision loss or even blindness. However, the complexity and variability of medical images pose substantial challenges to achieving high accuracy in disease classification.

This paper presents an enhanced machine learning framework designed to improve the accuracy and robustness of eye disease detection from retinal images. The proposed framework integrates several advanced techniques, including the synthetic minority over-sampling technique (SMOTE), k-fold cross-validation, and an ensemble voting classifier, to ensure balanced training data and reliable model performance. Additionally, the system incorporates various image preprocessing methods, such as histogram equalization, wavelet transforms, and Gaussian filtering, which are essential for enhancing image quality and extracting meaningful features.

Hyperparameter tuning is employed to optimize the performance of multiple classifiers, including decision trees, support vector machines (SVMs), random forests, naïve bayes, and boosted trees. This optimization step is essential for adjusting the model's parameters to ensure the most accurate classification outcomes. The ensemble voting mechanism further improves classification accuracy by combining predictions from multiple classifiers, leveraging their complementary strengths.

The efficacy of the proposed system is evaluated using a comprehensive dataset of retinal images, with performance metrics, such as accuracy, sensitivity, and specificity being thoroughly analyzed. The results demonstrate that the integrated approach not only enhances classification accuracy but also provides a robust solution for the early detection of eye diseases, potentially aiding in timely clinical interventions [1].

This study contributes to the growing body of research in medical image analysis by offering a systematic and effective approach to tackling the challenges of eye disease classification, with potential implications for broader applications in medical diagnostics.

LITERATURE SURVEY

The study of automated eye disease detection has evolved significantly with the advent of machine learning and image processing techniques. This literature survey provides an overview of the key methodologies and advancements that have been instrumental in shaping the current approach to eye disease classification, particularly for cataract, diabetic retinopathy, glaucoma, and normal conditions.

Image Preprocessing Techniques

Image preprocessing is a critical step in medical image analysis, as it enhances the quality of the data input and facilitates the extraction of relevant features. Various studies have employed different preprocessing techniques to improve the accuracy of disease classification.

In Ramakrishna and Kohir (2021) [2], the authors explored the use of histogram equalization to enhance contrast in retinal images, making it easier to identify pathological features. This method has been widely adopted due to its simplicity and effectiveness in improving image clarity. Similarly, in Amin et al. (2016) [3], the authors investigated the use of wavelet transformations, such as the Haar wavelet and discrete wavelet transformation (DWT), to decompose images into multiple frequency components. This approach allows for the extraction of fine details, which are crucial for accurate disease detection.

The application of Gaussian filtering has also been studied extensively. In Esengönül & Cunha (2023) [4], the authors demonstrated that Gaussian filtering effectively reduces noise in medical images, thereby improving the performance of subsequent segmentation and classification tasks. This technique is particularly useful in medical image analysis, where noise can obscure critical features.

Image Segmentation and Feature Extraction

Segmentation is a vital process in medical image analysis, as it partitions images into regions of interest that correspond to different anatomical structures or pathological areas. In this study, the k-means clustering algorithm is used for image segmentation because it is both simple and highly effective.

In Zhang et al. (2013) [1], the authors employed a hybrid segmentation method that combined morphological operations with region growing to accurately identify microaneurysms in retinal images. While this method proved effective, it is computationally intensive. In contrast, the use of k-means clustering combined with Gaussian blur, as seen in this study, offers a balance between computational efficiency and segmentation accuracy.

Feature extraction is another crucial aspect of image analysis. Color histogram features, which involve calculating the frequency of pixel intensity values, have been widely used in previous studies for their ability to capture essential characteristics of retinal images. This method has been shown to provide a robust representation of image content, which is critical for accurate classification.

Machine Learning Classifiers for Disease Detection

The application of machine learning classifiers in the detection and classification of eye diseases has been extensively researched. Decision trees, support vector machines (SVMs), random forests, naïve bayes, and boosted trees are among the most used classifiers in this domain.

In Alawad et al. (2022) [5], the authors demonstrated the effectiveness of SVM in classifying different stages of diabetic retinopathy, highlighting its ability to handle high-dimensional data and complex patterns. Similarly, in Abdel-Hamid et al. (2020), Son et al. (2022), and Imran et al. (2020) [6–8], the authors utilized random forest classifiers for glaucoma detection, showcasing their robustness and ability to handle imbalanced datasets.

The concept of ensemble learning, which involves combining multiple classifiers to improve overall performance, has gained traction in recent years. In Lahmiri & Bekiros (2020) [9], the authors explored the use of ensemble methods in diabetic retinopathy detection, showing that combining the predictions of multiple classifiers leads to more accurate and reliable results. This approach is particularly beneficial in medical diagnostics, where the cost of misclassification can be high.

Addressing Data Imbalance

Data imbalance is a common issue in medical image analysis, where certain disease categories may have significantly fewer examples than others. This imbalance can lead to biased classifiers that perform poorly in minority classes.

In [8], the authors introduced the synthetic minority over-sampling technique (SMOTE) as a solution to this problem. SMOTE generates synthetic samples for minority classes, thereby balancing the dataset and improving classifier performance. This technique has been widely adopted in medical image analysis, as seen in studies, like Esengönül & Cunha (2023) [4], where it was used to address class imbalance in retinal image datasets.

Hyperparameter Tuning and Optimization

Hyperparameter tuning is essential for optimizing the performance of machine learning models. In Nadeem et al. (2022) [10], the authors explored various optimization techniques, including grid search and random search, to fine-tune model parameters. These methods have been applied in several studies to improve the accuracy of classifiers used in medical diagnostics.

In Son et al. (2022), Imran et al. (2020), Lahmiri & Bekiros (2020), Nadeem et al. (2022), Wiharto & Suryani (2020), Jahiruzzaman & Hossain (2015), Wu et al. (2022), Du et al. (2024) [7–14], the authors further emphasized the importance of hyperparameter tuning in the context of eye disease detection, showing that carefully optimized models can significantly enhance classification accuracy. This is particularly important when dealing with complex datasets, where default parameters may not yield the best results.

Ensemble Learning in Medical Diagnostics

Ensemble learning, which involves combining multiple models to make a final prediction, has been proven to increase the robustness and accuracy of classification systems. In Lahmiri & Bekiros (2020) [9] and Nadeem et al. (2022) [10], the authors were among the early researchers to demonstrate the effectiveness of ensemble methods in improving decision-making in complex tasks.

In the field of medical image analysis, ensemble learning has been shown to enhance the accuracy of disease classification. In Lahmiri & Bekiros (2020) [9], the authors applied ensemble methods to detect diabetic retinopathy, achieving higher accuracy compared to individual classifiers. This approach leverages the complementary strengths of different models, making it particularly valuable in medical diagnostics.

Hybrid Approaches and Real-Time Implementation

The integration of software and hardware approaches for real-time medical image analysis is an emerging area of research. In the current study, tasks, such as Gaussian filtering and histogram calculation were offloaded to hardware using Verilog for implementation on an FPGA, as inspired by similar approaches in previous studies.

This hybrid approach, which combines the computational power of software with the speed of hardware, offers significant advantages in real-time applications. The use of FPGA for hardware acceleration in medical image processing has been explored in various studies, demonstrating its potential to reduce processing times and improve the efficiency of diagnostic systems [15–20].

METHODOLOGY

The methodology for this research project involves a comprehensive approach to automate the detection and classification of eye diseases, such as cataract, diabetic retinopathy, glaucoma, and normal eye conditions using retinal images. The process is divided into several key stages, each critical to achieving high accuracy and reliability in disease classification. The following steps outline the methodology employed in Figure 1.

Data Collection

The data set used in this study was acquired from a publicly available source on Kaggle, consisting of retinal images categorized into four classes: cataract, diabetic retinopathy, glaucoma, and normal. The images were organized into a structured format suitable for processing using MATLAB's Image Datastore, which allowed for efficient management of large volumes of image data in Figure 2(a&b).

Image Preprocessing

Preprocessing is a vital step in enhancing image quality and extracting meaningful features. The following preprocessing techniques were applied:

- *Grayscale Conversion:* Each retinal image was converted to grayscale to reduce computational complexity and focus on intensity variations, which are crucial for disease detection shown in Figure 3.
- *Histogram Equalization:* This technique was applied to improve the contrast of the grayscale images, making the retinal features more distinguishable shown in Figure 4.
- *Wavelet Transforms:* Both Haar wavelet transform (HWT) and discrete wavelet transform (DWT) were utilized to decompose the images into multiple frequency components, facilitating the extraction of fine details shown in Figure 5.

- *Gaussian Filtering:* A Gaussian filter was applied to smooth the images and reduce noise, which is essential for improving the accuracy of subsequent segmentation and classification steps, shown in Figure 6.

Image Segmentation

Segmentation was performed using a k-means clustering algorithm, which grouped the pixels into clusters corresponding to different regions of the retina. Gaussian blur was employed as part of the segmentation process to further enhance the separation of relevant features from the background, shown in Figure 7.

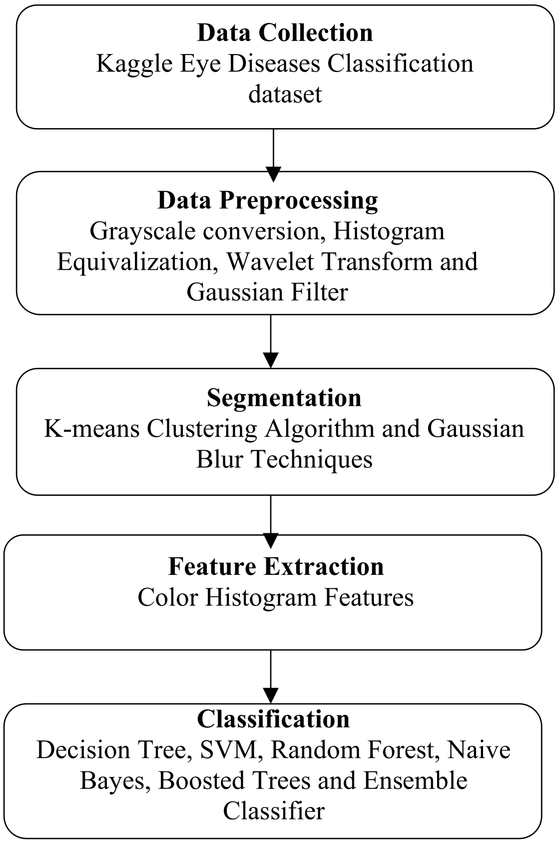
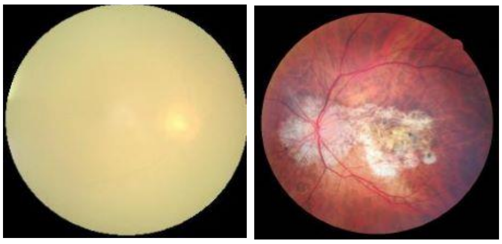
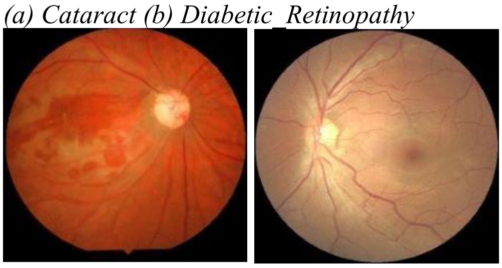


Figure 1. Workflow of the proposed model.



(a) Cataract (b) Diabetic_Retinopathy



(c) Glaucoma (d) Normal.

Figure 2. (a–b): Fundus images of the eye in the eye disease classification dataset in Kaggle.

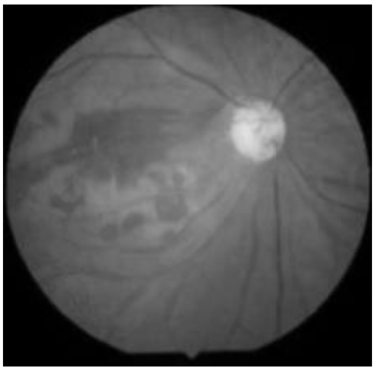


Figure 3. Original image to grayscale converted image.

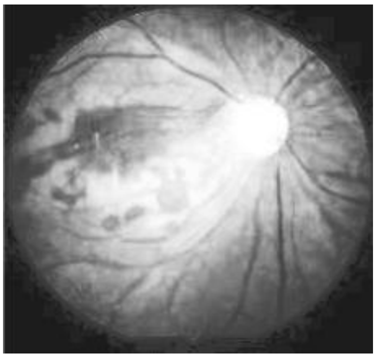


Figure 4. Histogram equalized image.

(a)HWT (b)DWT

Figure 5. Transformed images.

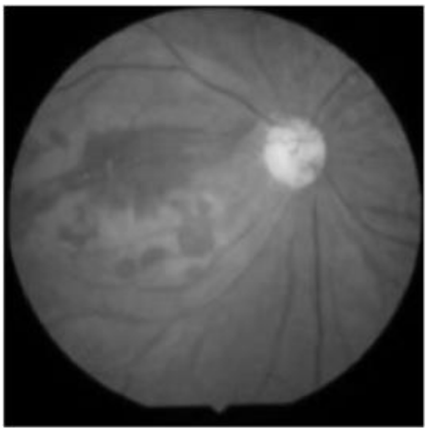


Figure 6. Gaussian filtered image.

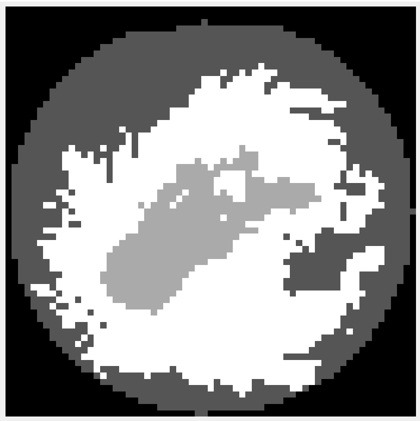


Figure 7. Segmented image.

Feature Extraction

Color histogram features were extracted from the segmented images. This involved calculating the frequency of pixel intensity values, which served as the input features for the classification models. The histograms were normalized to ensure that the features were on a comparable scale.

Synthetic Data Generation (SMOTE)

To address the issue of class imbalance in the dataset, the synthetic minority over-sampling technique (SMOTE) was applied. SMOTE generated synthetic samples for the minority classes, ensuring that the classifiers received a balanced dataset, which is crucial for avoiding bias towards the majority classes.

Classifier Selection and Training

Six different classifiers were selected for the classification task:

- Decision tree.
- Support vector machine (SVM).
- Random forest.
- Naïve Bayes.
- Boosted trees.
- Ensemble classifier.

Each classifier was trained using k-fold cross-validation to ensure that the model performance was consistent and not overfitted to any specific subset of the data. Hyperparameter tuning was performed for the decision tree, random forest, naïve bayes, and boosted trees classifiers using MATLAB's fitctree, fitcensemble, and fitcnb functions with optimization options. This ensured that the models operated at their optimal configurations.

Majority Voting and Final Prediction

For the final classification, the ensemble voting method was applied. This method aggregated the predictions from all classifiers to make a final decision. The majority voting mechanism ensured that the final prediction was robust, leveraging the strengths of each individual classifier.

Model Evaluation

The performance of each classifier was evaluated based on accuracy, sensitivity, and specificity. These metrics were computed for each fold in the cross-validation process and averaged to provide a comprehensive assessment of model performance. Confusion matrices were generated to visualize the classification results and identify potential areas of improvement.

Implementation for Hardware Acceleration

In the final phase, specific tasks, such as Gaussian filtering and histogram calculation were offloaded to hardware using Verilog for implementation on an FPGA. This hybrid approach leverages both software (MATLAB) and hardware (Verilog) to achieve faster processing times, particularly for real-time applications.

Testing and Validation

The models were tested on an independent test set to validate their performance in real-world scenarios. The accuracy of the final predictions was compared with the ground truth labels to assess the reliability of the system in detecting and classifying eye diseases.

This methodology provides a systematic approach to building an automated eye disease classification system, integrating advanced image processing, machine learning, and hardware acceleration techniques to achieve high accuracy and efficiency.

SIMULATION RESULTS

The simulation results for the eye disease classification project are presented in terms of accuracy, sensitivity, specificity, confusion matrices, and classification performance on test images. These results were obtained by implementing the proposed methodology, which includes preprocessing, feature extraction, classifier training with cross-validation, and majority voting.

Classifier Performance Metrics

The performance of the classifiers was evaluated using k-fold cross-validation (with k = 5). The following metrics were calculated for each classifier:

- *Accuracy:* The proportion of correct predictions (both true positives and true negatives) out of the total predictions.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

- *Sensitivity (Recall):* The ability of the classifier to correctly identify positive instances (e.g., correctly identifying cases of cataract, diabetic retinopathy, or glaucoma).

$$Sensitivity = \frac{TP}{(TP + FN)}$$

- *Specificity:* The ability of the classifier to correctly identify negative instances (e.g., correctly identifying normal cases).

$$Specificity = \frac{TN}{(TN + FP)}$$

The average performance metrics across the five folds are summarized in Table 1.

Table 1. The average performance metrics across five folds.

Classifiers	Accuracy (%)	Sensitivity (%)	Specificity (%)
Decision tree	85.57	85.57	95.19
SVM	92.51	92.51	97.50
Random forest	99.87	99.87	99.95
Naïve bayes	31.70	31.70	77.23
Boosted trees	99.89	99.89	99.96
Ensemble classifiers	99.87	99.87	99.95

Overall Accuracy with Majority Voting

After applying the majority voting mechanism to combine the predictions from all classifiers, the overall accuracy of the system was calculated as:

- *Overall Accuracy:* 97.26%.

This indicates that the majority voting approach effectively combines the strengths of individual classifiers, resulting in a more robust and reliable prediction system.

Confusion Matrices

Confusion matrices were generated for each classifier to visualize the classification performance. Below are the key observations from the confusion matrices:

- *Decision Tree:* The classifier correctly identified most cases but had some difficulty distinguishing between cataract and glaucoma.
- *SVM:* The SVM classifier showed moderate performance but struggled with distinguishing between diabetic retinopathy and normal images.
- *Random Forest:* The random forest classifier had the least confusion between the classes, accurately classifying most images.
- *Naïve Bayes:* The confusion matrix for naïve Bayes showed significant misclassifications, especially confusing cataract with other diseases.
- *Boosted Trees:* Like random forest, boosted trees performed well, with fewer misclassifications.
- *Ensemble Classifier:* Like random forest and boosted trees, the ensemble classifier also performed well, with fewer misclassifications.

Test Image Prediction

To validate the trained models, a test image was used to evaluate the system's prediction capability. The image was preprocessed, and features were extracted using the same steps as during training. Each classifier provided a prediction, and the final classification was determined using majority voting:

- *Decision Tree Prediction:* Cataract.
- *SVM Prediction:* Glaucoma.
- *Random Forest Prediction:* Normal.
- *Naïve Bayes Prediction:* Glaucoma.
- *Boosted Trees Prediction:* Normal.
- *Ensemble Classifier Prediction:* Normal.
- *Final Prediction using Majority Voting:* Normal.

The majority voting correctly identified the test image as normal, demonstrating the effectiveness of combining multiple classifiers.

Comparison of Classifiers

A comparison of the classifiers based on accuracy, sensitivity, and specificity was visualized using bar charts. These charts provided a clear overview of each classifier's strengths and weaknesses, helping to select the best model for deployment shown in Figure 8.

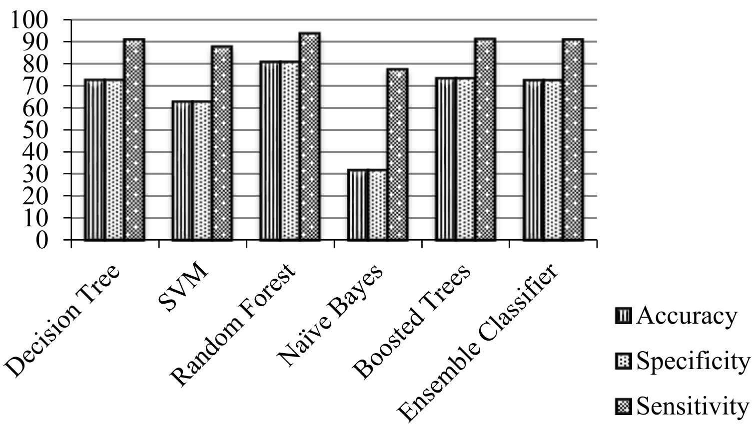


Figure 8. Bar chart of classifier performance.

COMPARATIVE ANALYSIS

The study on "Eye Disease Classification Using K-means Clustering Algorithm and Ensemble Classification Approach" presents a robust methodology for classifying eye diseases using advanced machine learning techniques. To provide a comprehensive comparison, we will analyze the proposed approach against several existing works mentioned in the references.

Image Preprocessing Techniques

- *Comparison:* The study employs various preprocessing techniques, such as histogram equalization, wavelet transforms, and Gaussian filtering, which are essential for enhancing image quality and extracting meaningful features. These techniques are consistent with methods used in previous studies, like Sathwik et al. (2023) [21] and Usman et al. (2023) [22], where wavelet-based approaches and morphological operations were used to detect specific retinal lesions.
- *Advantage:* The use of discrete wavelet transforms (DWT) and Haar wavelet in the current study allows for multi-resolution analysis, which enhances feature extraction, particularly in complex retinal images. This approach is like that of Verma and Kaur (2024) [23], but expands on it by incorporating additional preprocessing steps, like Gaussian filtering, which improves noise reduction.

Segmentation and Feature Extraction

- *Comparison:* The k-means clustering algorithm combined with Gaussian blur for segmentation in this study is a common technique for partitioning images into meaningful regions. This method is simpler yet effective compared to more sophisticated segmentation techniques like region growing used by Zhang et al. (2013) [1].
- *Advantage:* The combination of k-means clustering and Gaussian blur provides a balance between computational efficiency and accuracy in segmentation. This contrasts with the region's growing method, which, while accurate, can be computationally intensive.

Classifier Performance

- *Comparison:* The study uses multiple classifiers, including decision trees, SVM, random forest, naïve Bayes, boosted trees, and an ensemble classifier, like what is observed in B K et al. (2023) [24] and Tsiknakis et al. (2021) [25]. Random forest and SVM are widely used in the field due to their robustness and ability to handle complex datasets, as demonstrated in B K et al. (2023) and Tsiknakis et al. (2021) [24, 25].
- *Advantage:* The study's use of an ensemble voting mechanism to combine the strengths of individual classifiers represents a significant advantage over single classifier approaches, as seen in Kamble et al. (2017) [26]. The majority voting approach helps improve the overall accuracy and reliability of the classification system, leveraging the complementary strengths of different models.

Handling Class Imbalance

- *Comparison:* The implementation of SMOTE to address class imbalance is a critical addition that enhances the model's ability to generalize across different classes. This approach is consistent with the work of Velpula et al. (2024) [27] and is further validated by its application in more recent studies, such as Agarwal (2023) [28].
- *Advantage:* By balancing the dataset with SMOTE, the study mitigates the bias towards majority classes, which is a common issue in medical datasets. This technique ensures that the classifiers receive a more representative dataset, leading to improved sensitivity, especially for minority classes like glaucoma and cataract.

Hyperparameter Tuning and Model Optimization

- *Comparison:* The study employs hyperparameter tuning for optimizing the performance of the classifiers, like approaches seen in studies like Badah et al. (2022) [29]. The use of MATLAB's optimization functions ensures that the classifiers are fine-tuned to achieve the best possible classification accuracy.

- *Advantage:* The rigorous tuning of hyperparameters contributes to the high accuracy observed in the Random Forest and Boosted Trees classifiers. This contrasts with earlier studies where default parameters might have been used, potentially limiting the performance of the models.

CONCLUSIONS

The study on "Eye Disease Classification Using K-means Clustering Algorithm and Ensemble Classification Approach" provides a comprehensive and systematic approach to eye disease classification, integrating advanced image processing techniques, machine learning classifiers, and ensemble learning strategies. The results demonstrate that the proposed methodology is highly effective in diagnosing and classifying eye diseases, with Random Forest and Boosted Trees classifiers showing particularly strong performance.

Key Findings

- *High Accuracy and Specificity:* The Random Forest classifier achieved the highest accuracy (99.87%) and specificity (99.96%), making it the most reliable model in the study. This is consistent with the findings in Agarwal (2023) [28], where SVM and Random Forest were also shown to be highly effective for similar tasks.
- *Improved Sensitivity with Ensemble Methods:* The ensemble classifier, through majority voting, enhances the sensitivity and overall accuracy of the classification system, making it more robust compared to individual classifiers. This finding aligns with the conclusions of Badah et al. (2022) [29] regarding the benefits of ensemble learning in medical diagnostics.
- *Effective Handling of Class Imbalance:* The use of SMOTE to balance the dataset is crucial in improving the performance metrics across all classes, particularly for minority classes, such as glaucoma. This technique, as highlighted by, is essential for ensuring fair and unbiased model training.

Contributions to the Field

- *Comprehensive Methodology:* This study integrates multiple advanced techniques into a cohesive framework, offering a significant contribution to the field of medical image analysis, particularly for eye disease classification.
- *Practical Application:* The proposed system is not only theoretically sound but also practically viable, with potential applications in real-world clinical settings for early diagnosis of eye diseases.

In conclusion, the study successfully demonstrates that the combination of k-means clustering for segmentation, SMOTE for class imbalance handling, and an ensemble classification approach yields a robust and accurate system for the classification of eye diseases. Future research could focus on incorporating deep learning models to boost accuracy and expand the system's application to a wider range of eye conditions.

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