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Article

Improving cataract diagnosis using ensemble learning and modified random forest (MRF) classifier

Essaki Muthu Arumugam[1,*], Saravanan Krishnan[2]

[1] Department of Computer Science and Engineering, SCAD College of Engineering and Technology, Cheranmahadevi 627414, India
[2] Department of Computer Science and Engineering, College of Engineering, Guindy, Anna University, Chennai 600025, India
*** Corresponding author:** Essaki Muthu Arumugam, essakimuthua@outlook.com

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Abstract: This study explores modern techniques to enhance cataract detection accuracy, including ensemble learning, hybrid feature extraction, and a Modified Random Forest classifier. Traditional methods face limitations in feature extraction and classification, which are addressed through a hybrid approach combining LBP, GLCM, and CNN. LBP detects early-stage cataracts, GLCM captures spatial relationships, and CNN extracts deep structural features, improving image representation. The proposed Modified Random Forest (MRF) classifier integrates feature weighting and optimized decision thresholds, reducing noise and enhancing classification accuracy. Feature selection with Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA) minimizes overfitting and computational cost. Ensemble learning methods such as Bagging, Boosting, and Stacking further improve model robustness, with Stacking achieving 93% accuracy and high ROC-AUC for early-stage detection. However, computational complexity remains a challenge, particularly for deployment in clinical settings. KNN and SVM models underperform without feature selection, highlighting the need for careful preprocessing. Despite these challenges, the proposed techniques significantly improve cataract detection, ensuring better generalization across datasets.

Keywords: cataract detection, ensemble learning, hybrid feature extraction, modified random forest, bagging, boosting, stacking, classification accuracy, ROC-AUC, medical imaging

1. Introduction

Cataracts cause the lens of the eye to gradually fog, which is a major global health concern. This is particularly true in countries with limited access to healthcare services that are middle and lower-income. The World Health Organization estimates that cataracts afflict millions of individuals globally and account for around 51% of all incidents of blindness. Because resources may be scarce in these locations, the impact is particularly severe, underscoring the urgent need for better diagnostic and intervention methods. Early detection and prompt treatment are critical to preventing irreversible vision loss and improving the quality of life for those affected by visual impairments. Therefore, it is essential to treat this common cause of visual impairment by coordinated initiatives to increase awareness, enhance accessibility to eye care services, and promote international cooperation. A common eye condition called cataracts is characterized by clouding of the camera lens, which makes it difficult for light to flow through and impairs vision [1].

Eye scans are processed digitally to determine whether cataracts are present and how severe they are. Two different techniques are used to handle a dataset that includes images of eyes with different degrees of cataract [2]. Semantic segmentation for the identification and location of surgical equipment and anatomical components is a basic component of such capabilities [3]. The segmentation models' overall performance was enhanced using the AWTFE technique, which efficiently finds features pertinent to the pupil region [4].

The fluctuation range of accuracies is becoming steadier, and the DCNN classification accuracies are getting better. The approach achieved the maximum accuracy of 93.52% in cataract identification and 86.69% in grading tasks [5]. The following clearly explains the main contributions of this work:

The proposed MRF model combining LBP, GLCM, and CNN improves image representation by capturing texture, spatial relationships, and deep structural features for better cataract detection.

Enhances classification accuracy by integrating feature weighting and optimized decision thresholds, reducing noise, and improving sensitivity.

Techniques like Bagging, Boosting, and Stacking improve model performance, with Stacking achieving 93% accuracy and high ROC-AUC for early-stage cataract detection.

RFE and PCA help minimize overfitting and computational cost, but deploying complex models in clinical settings remains a challenge, emphasizing the need for efficient preprocessing.

The remaining portion of this document is summarized as follows: In Sections 1 and 2, the introduction and relevant literature were found; Section 3 goes into additional detail about the proposed methodology, Section 4 presents the experimental results, and Section 5 looks at the conclusions and possible directions for further study.

2. Related works

Cruz et al [6] have proposed, age and illness are two factors that can cause the ocular nucleus to become opaque, a condition known as a cataract. Computational intelligence methods are essential for helping medical pre-diagnosis specialists automatically categorize and grade illnesses. Conventional image processing algorithms are used to process and extract pertinent features. Manuel et al. [7] have recommended, to collect 1000 Kaggle retinal images, which will then be split equally between two groups: those with and without cataracts. A variety of neural networks, such as ResNet18, ResNet34, InceptionResNetV2, and InceptionV4, are then used to accurately classify the images.

Zhang et al. [8] have suggested, RCRNet outperforms and is more efficient than the most sophisticated channel attention-based networks, as demonstrated by two publicly available medical datasets and the AS-OCT-NC2 dataset. Cheng et al. [9] have discussed, the images are then recovered using the novel SGRIF model based on attenuation and scattering. Navatha et al. [10] have introduced, an automated cataract detection technique that uses the Adam optimizer-optimized VGG-19 convolutional neural network (CNN) model. Using images from digital cameras.

Shi et al. [11] have reported, a surgeons can identify risk factors for pupillary instability before surgical issues arise by using automated pupil segmentation from surgical recordings. Vadduri et al. [12] have proposed, using cutting-edge deep learning techniques, the Deep Attention U-Net for Cataract Diagnosis (DAUCD) model enhances the segmentation and classification of cataract in retinal pictures.Xiong et al. [13] have proposed, the pre-trained ResNet is used to extract high-level features, while a GLCM is used to extract texture data. The two feature types are then blended through a dimension expansion procedure where texture feature vectors are added to the tail of high-level feature vectors.

Zhang, et al. [14] have suggested, to separate cataract identification and grading tasks yielded 93.52% and 86.69%, respectively. The performance of the DCNN classifier is shown in this research to be superior to the state-of-the-art. Imran et al. [15] have reported, the pre-trained residual network (ResNet) is utilized to extract high-level features, while a GLCM is used to extract texture data.

3. Proposed system

The procedures for cataract grading will be covered in this section. The proposed framework for cataract levelling is shown in **Figure 1**.

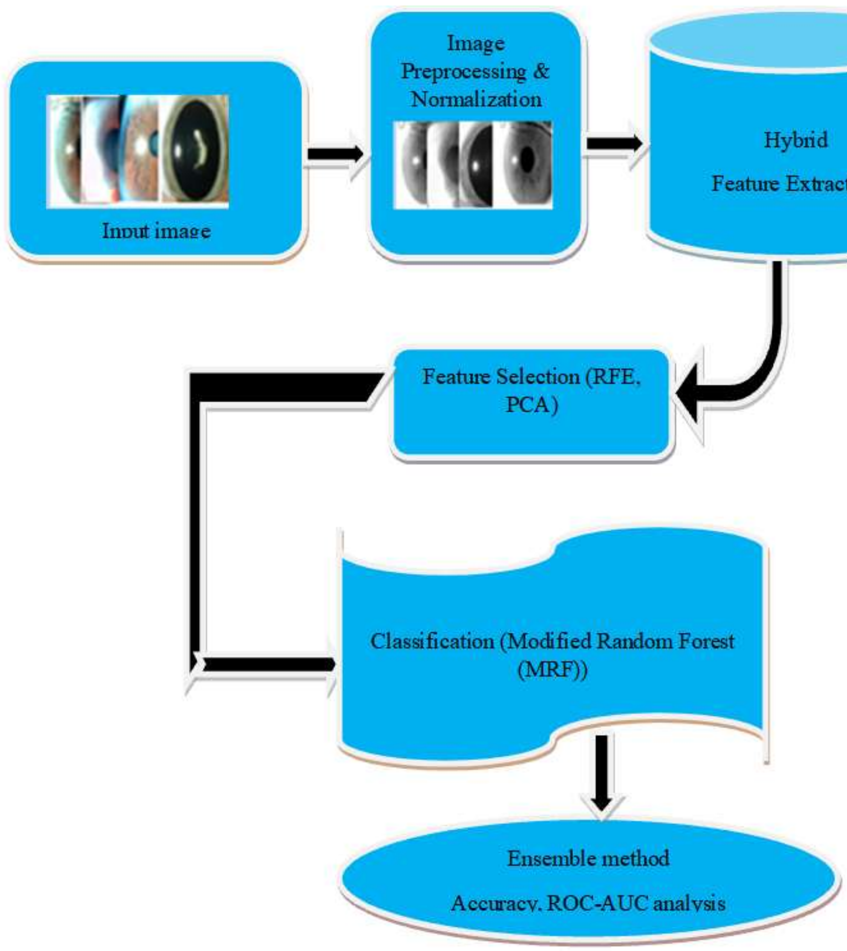

Figure 1. Block diagram proposal for cataract categorization.

The figure illustrates a machine learning-based image classification pipeline. It begins with an input image, which undergoes Image Acquisition & Preprocessing to enhance its quality and remove noise. The processed image then proceeds to Hybrid Feature Extraction, where different techniques are used to extract meaningful features for further analysis. Next, Feature Selection methods such as RFE and PCA are applied to reduce dimensionality and retain the most relevant features. The refined features are then fed into the Classification stage, where a MRF classifier is employed to categorize the image. Ensemble learning methods such as Bagging, Boosting, and Stacking further improve model robustness. Finally, the model's performance is evaluated using Accuracy and ROC-AUC analysis, which assess the classification effectiveness and reliability.

3.1. Image pre-processing

Pre-processing prepares the images for analysis, which makes it crucial for cataract identification. Min-Max Normalization, Median Filtering, and Contrast Limited Adaptive Histogram Equalization (CLAHE) were the three main techniques that used for this. The included 410 images, 196 of which had cataract damage and 214 of which were normal. These approaches equalize brightness levels, remove noise, and improve contrast [16]. This facilitates classifiers by purifying the input data, which makes it simpler to identify even the slightest variations between eyes in good health and those with cataracts. It is crucial to have clean, well-prepared data because it improves feature extraction and makes the classifiers' work easier.

3.1.1 Image normalization

This guarantees that, regardless of the initial method of capture, the traits we wish to examine are present in every image. Min-Max Normalization is calculated using the following formula:

$$x' = x - \frac{\min(x)}{\max(x) - \min\,(x)} \tag{1}$$

where, X is the original pixel value, X' is the normalized pixel value, Max(x) and min(x) are the image's minimum and maximum pixel values, respectively.

3.2. Texture-based feature extraction

Statistical texture analysis is a widely used image processing-based method for analyzing medical imaging textures, such as cataracts. This is because relevant information about our textured tissues is provided by tissue features [17]. Both LBP and GLCM, two widely used statistical techniques for texture analysis, are discussed in this chapter. In order to accurately detect cataracts, these techniques are crucial for capturing the differences in texture and spatial correlations in images.

3.2.1. Local binary pattern (LBP)

An LBP is one method of representing textural features in images, as seen in **Figure 2**. With this method, a specific pixel is effectively represented by thresholding with its neighbors inside a neighborhood known as Lattice points.

LBP uses the gray level of the central pixel, which is determined by the following equation, to determine a threshold value for each nearby pixel:

$$LBP_{A,B}(x, y) = \sum_{a=0}^{A-1} S(l_a - l_c) \cdot 2^a \tag{2}$$

where

$$S(l_a - l_c) = \begin{cases} 1, if\ l_a \ \geq l_c \\ 0, if\ l_a < l_c \end{cases} \tag{3}$$

where, l_c is the gray value of the central pixel, l_a (for a = 0,1, 2…, A−1) denotes the neighboring pixels located along a circle of diameter $C/2$ (where $C/2>1$), with the number of neighbors denoted as A (where $A > 1$), The term 2^a represents the binomial factor assigned for each value of la.

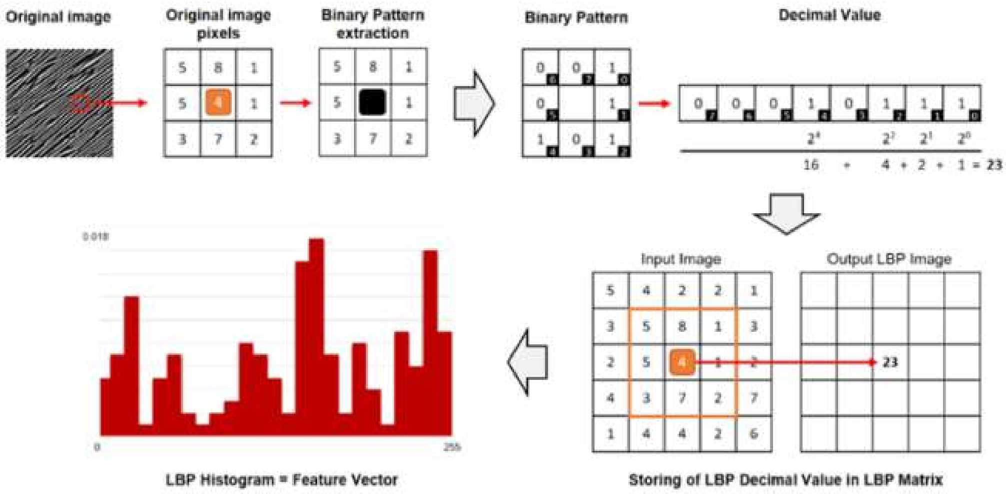

Figure 2. Local binary pattern.

3.2.2. GLCM (gray level co-occurrence matrix)

The GLCM is a statistical tool that illustrates the relationships between various image pixels. Its primary purpose is to ascertain the frequency with which specific greyscale combinations (pixel brightness values) occur in photographs, a task that is frequently encountered in image processing and computer vision. The entries $P(i, j, d, \theta)$ in the matrix indicate the likelihood that a pixel with value ii will be adjacent to a pixel with value j at distance dd and orientation θ. A solid foundation for computing a variety of texture properties is provided by the GLCM's ability to capture such spatial relations. One well-liked technique for texture analysis in medical imaging, such as cataract identification, is GLCM, one of the earliest types [18]. GLCM offers a number of textural characteristics that can be crucial in distinguishing between normal and cataract-affected lenses.

3.2.3. CNN

CNNs are able to capture high-level abstract features that are difficult to detect using conventional techniques, like overall opacities or massive structural deformations.

3.3. Modified random forest classifier

The cataract image can be retrieved with unique characteristics thanks to hybrid feature extraction, which integrates CNNs, GLCM, and LBP:

LBP: Because local binary patterns are utilized to record local texture patterns, they are useful for identifying subtle changes that occur at the edges of smooth areas in the early stages of cataract development.

GLCM: By recording the differences in pixel intensities inside an image with respect to their closest neighbors, it aids in the classification of lens cloudiness and opacity.

CNN: Because high-level abstract features that are difficult to identify using conventional techniques, including overall opacities or significant structural deformations, are captured by CNNs.

While Random Forests (RF) are a classic classifier, Modified Random Forests (MRF) are a method that has been tuned to operate better with biomedical datasets like cataract images. The classifier function is mostly reliant on what has been specified by enhancing its focus, which means that highly discriminative CNN and LBP features are likely targets in a weighted feature selection context (MRF provides greater weights to more informative) [19]. Feature splitting is the process of selecting features (by default, they are chosen at random) using node-based theory and Gini impurity calculations, which aid in creating optimal decision boundaries. Decision thresholds that are dynamically modified throughout the tree build sequence improve class separation, particularly in extremely unbalanced data sets and subtypes. The following formula determines each feature ff's feature significance weighting:

$$W_f = \frac{\left\{\sum_{\{t=1\}}^{\{T\}} I(f,t)\right\}}{\{T\}} \tag{4}$$

where, W_f represents the weight assigned to feature ff, T is the total number of trees in the forest, $I(f, t)$ is an indicator function that returns 1 if feature f is used in tree t, and 0 otherwise. Gini Impurity for Feature Splitting Equation:

$$(t) = 1 - \sum_{\{c=1\}}^{\{C\}} (p_C(t))^2 \tag{5}$$

where, $G(t)$ is the Gini impurity at node tt, $p_c(t)$ represents the proportion of samples belonging to class c at node t. The modified Random Forest algorithm is described in Algorithm 1.

Algorithm 1: Pseudocode for modified random forest algorithm

```
# Inputs: Cataract image dataset (X), Labels (Y)
# Output: Trained Modified Random Forest Model (MRF)
Initialize empty feature set F and empty forest MRF
For each image in the dataset X:
    Step 1: Extract LBP features
    Step 2: Extract GLCM features
    Step 3: Extract CNN features
    Step 4: Concatenate LBP, GLCM, and CNN features into combined_features
F.append (combined_features)
For each tree in the forest:
    Step 1: Select a weighted subset of features based on feature importance
    Step 2: Construct the decision tree using optimized feature splits and thresholds
    Step 3: Add the constructed tree to the forest MRF
Return the final MRF model
```

3.4. Ensemble learning: Bagging, boosting, and stacking

Multiple separate models, or base learners, are combined in ensemble learning approaches to improve performance, generalization, and resilience [20]. According to these approaches, numerous inferior models are combined to address a single model's shortcomings, such as overfitting and insufficient capacity. Hopefully, they can cover this by bringing in a large number of more capable students. Because medical picture collections contain intricate patterns and imbalances, the ensemble approaches of bagging, boosting, and stacking is crucial. By combining the characteristics of many models, ensemble learning in cataract detection enables us to create more reliable and effective classifiers.

By training several instances of the same base classifier on various subsamples of data, the ensemble technique known as "bagging" (Bootstrap Aggregating) seeks to lower the variance of a machine learning model. Creating subsets from the original dataset by sampling with replacement is known as bootstrapping in the context of this approach. In **Figure 3** shows that the flowchart of ensemble approach for cataract classification.

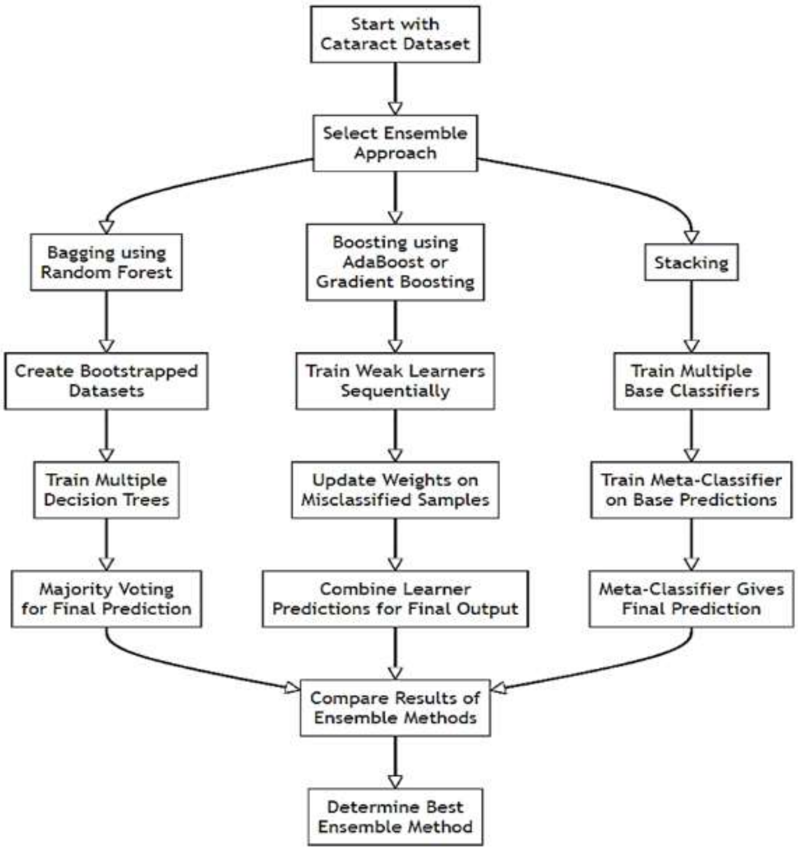

Figure 3. Flowchart of ensemble approach for cataract classification.

The "boosting" ensemble strategy reduces the model error by training a series of ineffectual learners, each of which tries to correct the previous one. On examples that are challenging to categorize, Bagging appears to train each model separately, enhancing rather than improving the performance of weak learners.

Stacking is an improved ensemble technique in which a meta-classifier is used to combine the predictions of many base classifiers that have been trained to get a single final result. In Stacking, predictions from many algorithms are combined with a final model trained to determine how it should be carried, as opposed to Bagging and Boosting, which fit the base classifiers separately or sequentially.

3.5. Performance evaluation

The models' performance in terms of five key metrics—accuracy, precision, recall, F1 score, and ROC-AUC—are detailed in this section. For each of the three datasets, we evaluate the model independently. Evaluation Metrics:

Accuracy: Measures the overall correctness of the model.

Precision: Important in medical diagnostics to reduce false positives.

Recall: Ensures that all true positive cases are identified.

F1 Score: Combines precision and recall, useful in scenarios with imbalanced datasets.

ROC-AUC: Reflects the model's discrimination ability across various thresholds.

4. Experimental result and discussion

The performance of numerous machine learning models is thoroughly reviewed in this section with an emphasis on feature extraction techniques, classification strategies, and ensemble-based approaches. Employing three Cataract datasets, one can assess this analysis utilizing precision, recall, accuracy, F1 score, and ROC-AUC. The significance level of each feature that is taken from images and its contribution to model efficacy are displayed by Feature Importance Analysis, one of these studies.

4.1. Dataset description

Three handwritten datasets that offer different difficulties for image identification and classification can be used to separate the data, giving a clear picture of the computing power of each model: These datasets are used to test the effectiveness of various feature extraction and classification techniques, with an emphasis on the models' generalizability across various stages of cataract development shown in **Table 1**.

Table 1. Dataset description.

Dataset	Description	Total images	Cataract images	Normal images
Cataract Dataset 1	Comprises both early and advanced phases of cataracts, offering a wide range of severity levels for reliable testing.	2112	1038	1074
Cataract Dataset 2	They were designed to evaluate the models' ability to differentiate between fully formed and immature cataracts, a feature that is useful for clinical staging.	410	214	196
Cataract Dataset 3	mostly comprises of normal images with a small percentage of early-stage cataracts to test the accuracy of early diagnosis.	400	100	300

4.2. Results for all datasets

Dataset 1: Stacking and Bagging emerged victorious, with Stacking leading in both acc (93%) and ROC-AUC (94%). This remarkable level of behavior was enhanced by the Base Layer in Stacking, which included classifiers like Random Forest and SVM [21]. The performance charts of the machine learning model on Dataset 1, which is a classification of simple cataracts from mild to severe cases, are shown **Figure 4**.

The line plot below displays the accuracy, precision, recall, F1 Score, and ROC-AUC performance of several ML models on Dataset 1. As can be seen in the following graphic, stacking consistently appears to perform better than the others; when totaled, this indicates that stacking has the best accuracy (93%), recall (94%), and ROC-AUC score (94%). While still exhibiting excellent behavior, Bagging and Boosting lag behind Stacking in terms of recall and global accuracy. KNN and SVM perform badly when utilizing traditional methods, especially in recall, because low ROC-AUC values are likely to make it more difficult to identify subtle cataract characteristics.

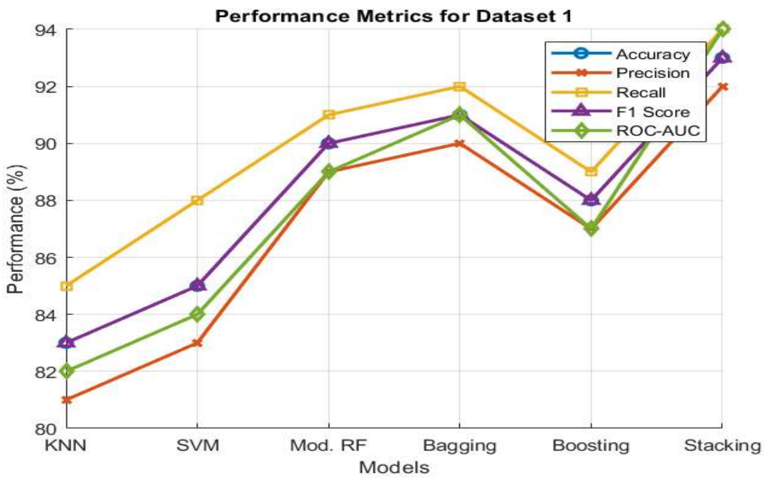

Figure 4. Performance of various machine learning models on Dataset 1.

Dataset 2: Identifying immature and adult cataracts was difficult, and the ensemble approach may have done the best in this regard, with Stacking obtaining an F1-score of 91%. Distinguish between several types of cataracts in the next figures, which display the performance of base models on Dataset 2 shown in **Figure 5**. This dataset assesses the models' ability to detect changes in cataracts at different stages. This line plot illustrates how well the model performed across Dataset 2 in differentiating between immature and mature cataracts.

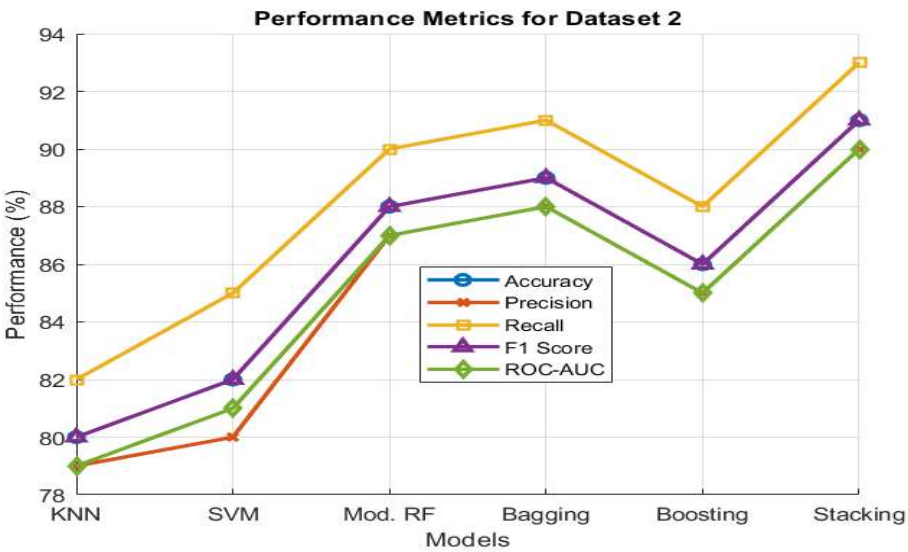

Figure 5. Performance of various machine learning models on Dataset 1.

The stacking model outperforms all other models in determining the stage at which a cataract has grown, achieving the highest forecasts for accuracy (91%) and recall (93%). The stacking ensemble produces the best F1 scores and precision, followed by Modified Random Forest and Bagging, which perform almost as well but fall short of stacking. This data set clearly shows the performance difference between ensemble technique parameters (boosting, bagging, stacking) and standard models (KNN and SVM).

Dataset 3: Stacking and Modified Random Forest are the best in terms of True Positive/False Positive rates, as is typical. The inability of the models to detect early-stage cataracts makes it clear that they have a lot more trouble with Dataset 3 shown in **Figure 6**, which is full of normal photos, than the other two. The models trained with Dataset 3, an out-of-distribution collection (the job emphasis is to diagnose early-stage cataracts in practically normal photos), are displayed in a line plot. With an accuracy of 92% and a ROCAUC of 91%, stacking performed the best, showing great promise for identifying even minute cataract signs in a difficult sample. Although they both perform rather well, bagging and boosting fall a little short of stacking.

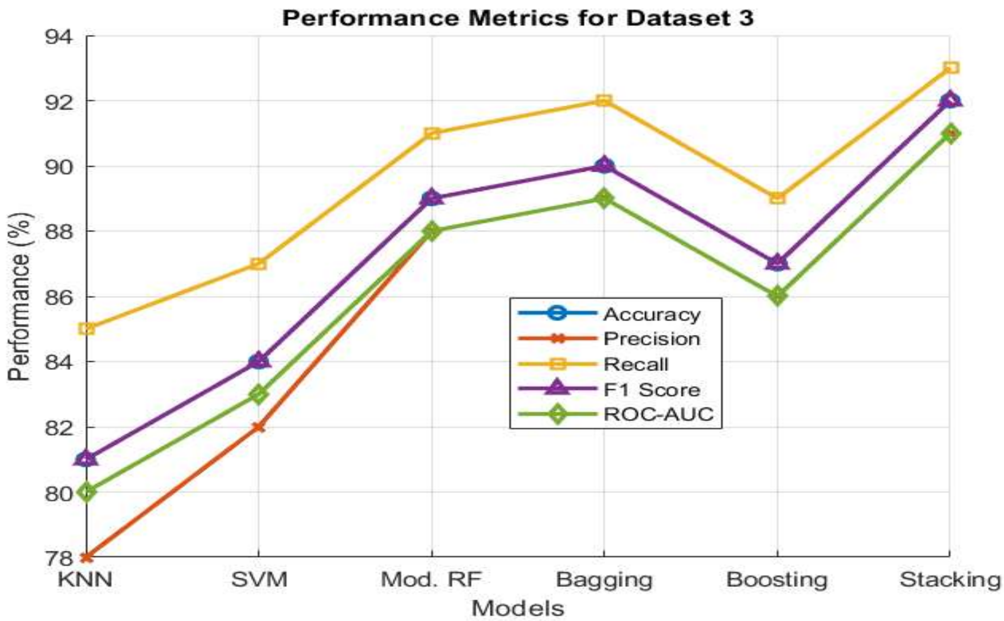

Figure 6. Performance of various machine learning models on Dataset 1.

Traditional models like KNN and SVM perform poorly in differentiating between normal and early-stage cataract images, as evidenced by lower recall and ROC-AUC scores [22]. **Table 2** shows the model results for each of the three datasets. These measures are critical in understanding how well the algorithms detect cataracts at different stages and generalize to unidentified data.

Table 2. Performance metrics across all datasets.

Model	Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	ROC-AUC (%)
	Dataset 1	83	81	85	83	82
KNN	Dataset 2	80	79	82	80	79
	Dataset 3	81	78	85	81	80

Table 2. (*Continued*).

Model	Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	ROC-AUC (%)
SVM	Dataset 1	85	83	88	85	84
	Dataset 2	82	80	85	82	81
	Dataset 3	84	82	87	84	83
Modified Random Forest	Dataset 1	90	89	91	90	89
	Dataset 2	88	87	90	88	87
	Dataset 3	89	88	91	89	88
Bagging	Dataset 1	91	90	92	91	91
	Dataset 2	89	88	91	89	88
	Dataset 3	90	89	92	90	89
Boosting	Dataset 1	88	87	89	88	87
	Dataset 2	86	85	88	86	85
	Dataset 3	87	86	89	87	86
Stacking	Dataset 1	93	92	94	93	94
	Dataset 2	91	90	93	91	90

5. Conclusion

In order to increase the accuracy of cataract detection, this study investigated contemporary methods such as ensemble learning, hybrid feature extraction, and Modified Random Forest. The hybrid technique (LBP, GLCM, and CNN) improved picture representation, but the proposed Modified Random Forest, which includes feature weighting and adjusted decision thresholds, reduced noise and increased sensitivity. Ensemble approaches such as bagging, boosting, and stacking improved accuracy even more, with stacking attaining 93% for early-stage cataract identification. Feature selection and dimensionality reduction helped to reduce overfitting and computational costs, but applying high-computational models in clinical contexts remains challenging. Future study could look into AutoML for feature selection, deep learning upgrades, and model optimization for real-time applications through pruning and quantization. Overall, combining improved feature extraction, optimal classification, and dimensionality reduction greatly improves cataract detection, laying the groundwork for future medical image analysis breakthroughs.

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References

1. Ismail WN, Alsalamah HA. A novel CatractNetDetect deep learning model for effective cataract classification through data fusion of fundus images. Discover Artificial Intelligence. 2024; 4(1): 54. doi: 10.1007/s44163-024-00155-y
2. Jindal I, Gupta P, Goyal A. Cataract detection using digital image processing. 2019 global conference for advancement in technology (gcat). IEEE publishing; 2019. pp. 1–4. doi: 10.1109/gcat47503.2019.8978316
3. Grammatikopoulou M, Evangello F, Abdolrahim K, et al. CaDIS: Cataract dataset for surgical RGB-image segmentation. Medical Image Analysis. 2021; 71 (2021): 102053. doi: 10.1016/j.media.2021.102053
4. Giap BD, Srinivasan K, Mahmoud O, et al. Adaptive Tensor-Based Feature Extraction for Pupil Segmentation in Cataract Surgery. IEEE Journal of Biomedical and Health Informatics. 2024; 28(3): 1599–1610. doi: 10.1109/jbhi.2023.3345837
5. Zhang, L, Li J, Han H, et al. Automatic cataract detection and grading using deep convolutional neural network. In: Proceeding of 2017 IEEE 14th international conference on networking, sensing and control (ICNSC); 2017. pp. 60–65.
6. Cruz-Vega I, Hans I, Juan M, et al. Nuclear cataract database for biomedical and machine learning applications. IEEE Access. 2023; 11(2023): 107754–107766. doi: 10.1109/ACCESS.2023.3312616
7. Manuel FME, Saide SM, Ali FDMA, et al. Ocular Cataract Identification Using Deep Convolutional Neural Networks. In:Proceeding of 2023 International Conference on Artificial Intelligence, Big Data, Computing and Data Communication Systems (icABCD); 2023. pp. 1–5.
8. Zhang X, Xiao Z, Yang B, et al. Regional context-based recalibration network for cataract recognition in AS-OCT. Pattern Recognition. 2024; 147: 110069. doi: 10.1016/j.patcog.2023.110069
9. Cheng J, Li Z, Gu Z, et al. Structure-preserving guided retinal image filtering and its application for optic disk analysis. IEEE Transactions on Medical Imaging. 2018; 37(11): 2536–2546. doi: 10.1109/tmi.2018.2838550
10. Navatha N, Revanth A, Pramod C, et al. High-Accuracy Cataract Detection using Enhanced VGG-19 CNN and Adam Optimizer[C]//2024 IEEE 6th International Conference on Cybernetics, Cognition and Machine Learning Applications (ICCCMLA); 2024. pp. 117–122.
11. Shi X, Zhang D, Liang S, et al. Real-time corneal image segmentation for cataract surgery based on detection framework. International Journal of Computer Assisted Radiology and Surgery. 2025; 1-10. doi: 10.1007/s11548-025-03506-x
12. Vadduri M. DAUCD: Deep attention U-Net for cataract detection leveraging CNN frameworks. International Journal of Intelligent Engineering & Systems. 2025; 18(1): 184–197. doi: 10.22266/ijies2025.0229.15
13. Xiong Y, He Z, Niu K, et al. Automatic cataract classification based on multi-feature fusion and SVM. In: Proceeding of 2018 IEEE 4th International Conference on Computer and Communications (ICCC); 2018. pp. 1557–1561.
14. Zhang L, Li J, Han H, et al. Automatic cataract detection and grading using deep convolutional neural network. In: Proceeding of 2017 IEEE 14th international conference on networking, sensing and control (ICNSC); 2017. pp. 60–65.
15. Imran A, Li J, Pei Y, et al. Cataract Detection and Grading with Retinal Images Using SOM-RBF Neural Network. In: Proceeding of 2019 IEEE Symposium Series on Computational Intelligence (SSCI); 2019. pp. 2626–2632.
16. Manchalwar MD, Warhade KK. Histogram of Oriented Gradient based Automatic Detection of Eye Diseases. 2017 International Conference on Computing, Communication, Control and Automation (ICCUBEA); 2017. pp. 1–5.
17. Faizal S, Rajput CA, Tripathi R, et al. Automated cataract disease detection on anterior segment eye images using adaptive thresholding and fine tuned inception-v3 model. Biomedical Signal Processing and Control. 2023; 82: 104550. doi: 10.1016/j.bspc.2022.104550
18. Laia F H, Buulolo P. Application of svm and lda models in eye image-based cataract detection system. Jurnal ICT: Information and Communication Technologies, 2024, 15(2): 98–106.
19. Sevani N, Tampubolon H, Wijaya J, et al. A Study of Convolution Neural Network Based Cataract Detection with Image Segmentation. In: Proceeding of 2022 IEEE International Conference on Communication, Networks and Satellite (COMNETSAT); 2022. pp. 216–221.
20. Syarifah MA, Bustamam A, Tampubolon PP. Cataract classification based on fundus image using an optimized convolution neural network with lookahead optimizer. In: Proceeding of AIP Conference Proceedings; 2020.

21. Cao L, Li H, Zhang Y, et al. Hierarchical method for cataract grading based on retinal images using improved Haar wavelet. Information Fusion. 2020; 53: 196–208. doi: 10.1016/j.inffus.2019.06.022
22. Gu H, Guo Y, Gu L, et al. Deep learning for identifying corneal diseases from ocular surface slit-lamp photographs. Scientific Reports. 2020; 10(1): 17851. doi: 10.1038/s41598-020-75027-3