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ENSEMBLE DEEP LEARNING MODELS WITH HARD VOTING FOR ACCURATE CATARACT CLASSIFICATION USING FUNDUS IMAGES

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Abstract
Cataracts are among the world's most prevalent eye conditions and one of the main reasons for blindness, especially in older people. Immediate and proper diagnosis is important because cataracts are very curable through surgery if diagnosed in time. However, specialists are not readily available in the majority of the regions, thus leading to delays in diagnosis. To address this challenge, the latest research has greatly focused on applying automated, AI based diagnostic systems. Our study proposes an ensemble-based classification framework based on three pre trained convolutional neural networks VGG16, Xception, and DenseNet121 to classify cases of cataract and normals from retinal fundus images. 1,038 cataract and 1,074 normal images were captured from diverse public datasets, including IDRiD, Ocular Recognition, and HRF. Data augmentation techniques were applied prior to model training to prevent overfitting. Final classification utilized majority voting across the three models, enhancing stability without compromising model bias. The ensemble technique achieved optimal results with 100% accuracy, which implies its high capability in supporting cataract screening and early intervention

INTRODUCTION

Cataracts are a leading cause of blindness worldwide, responsible for tens of millions of cases of visual impairment [1]. This condition, characterized by clouding of the eye's lens, is treatable with surgery, but early diagnosis is critical to prevent irreversible vision loss. However, early cataract development can hardly be detected without the help of a slit-lamp biomicroscope or ophthalmoscopy. A cataract can only appear gray/white or cloudy to others when it is very large (mature or hypertrophic).

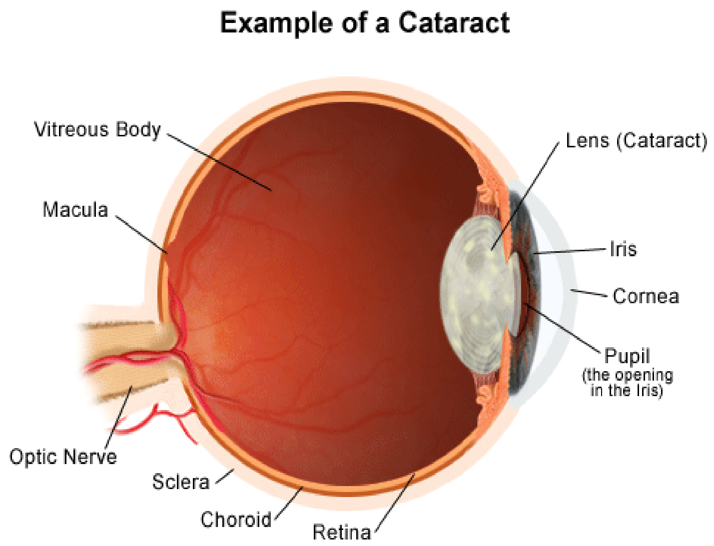


Fig. 1. Anatomical image *of a cataract-affecte eye.*[49

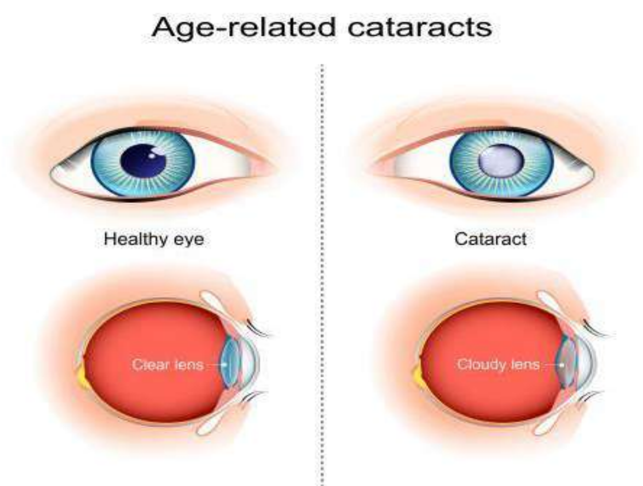


Fig. 2. Visual image *of a cataract-affected eye.*[50]

In many regions, however, cataracts often go undetected or untreated until advanced stages due to limited access to ophthalmic care. Only about 17% of people with vision impairment due to cataract receive timely intervention. These gaps highlight the need for accessible, efficient screening methods to identify cataracts early and guide patients toward proper treatment[1]. Traditionally, cataract detection requires an in-person eye examination by an ophthalmologist. Examinations are resource intensive and not always feasible for large scale screening or remote communities. In contrast, color fundus photography noninvasive imaging of the retina is widely performed even outside specialist clinics and could be repurposed for cataract screening [2]. Indeed, studies have noted that blurred retinal photographs and reduced visibility of blood vessels are characteristic of cataract presence, whereas clear visualization of fine retinal details usually indicates the absence of significant cataract [3]. Leveraging such subtle cues, an automated system could detect cataracts from standard retinal images, providing a convenient screening tool that integrates into existing eye care workflows.

Despite advancements, building a reliable automated cataract detection system still encounters multiple challenges. One of the main obstacles is the scarcity of data large, annotated datasets of cataract fundus images are often limited. Annotating medical images is a time-consuming task, and datasets specific to cataracts are typically small and exhibit imbalanced class distributions [4]. This limitation can lead deep learning models to overfit and perform poorly when generalizing to new data. Moreover, variability in image quality and patient demographics adds complexity. Fundus images can vary in resolution, lighting conditions, and field of view based on the imaging equipment used, while patients may present additional co-existing ocular conditions or post-surgical changes [5]. Consequently, models must be capable of handling such inconsistencies, as performance on one dataset may not seamlessly translate to another. Since cataracts affect fundus images indirectly, the models must be able to detect subtle visual differences and distinguish them from other forms of image degradation. Addressing these challenges involves employing strategic design approaches such as transfer learning, data augmentation, and sophisticated model architectures aimed at better generalization. Utilizing transfer learning from models pre-trained on large-scale datasets is a widely adopted method to counteract the lack of extensive medical data [6], while data augmentation techniques help to artificially increase dataset size and variability, thus enhancing model robustness.

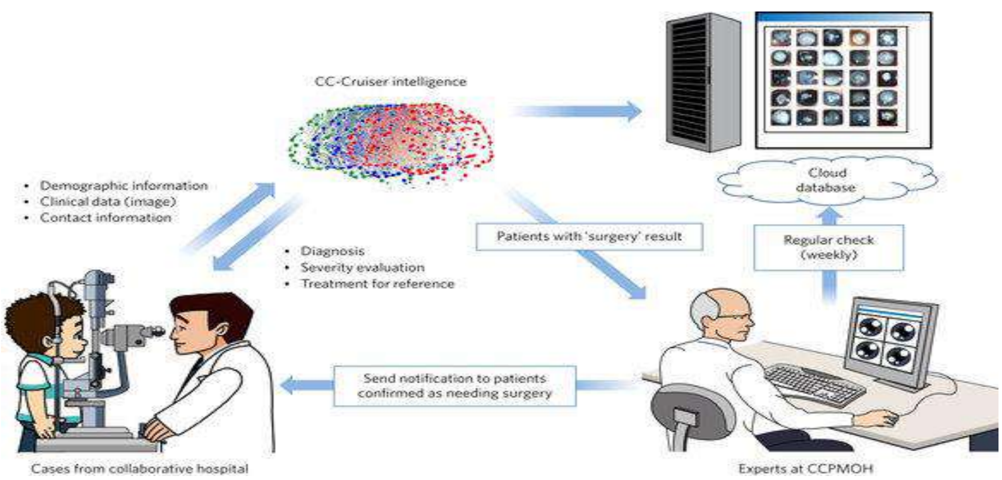


Fig. 3: Workflow of the CC-Cruiser Intelligence System for Cataract Diagnosis and Surgical Triage[51]

In recent years, deep learning and convolutional neural networks in particular has revolutionized medical image analysis, including ophthalmic diagnostics [7]. CNN based algorithms can learn to recognize complex patterns in images, exceeding human performance in some tasks and offering consistency and speed in analysis. Successful applications in ophthalmology include automated detection of diabetic retinopathy, glaucoma, and age-related macular degeneration from fundus photos [8]. Researchers have turned to deep learning for cataract detection using fundus images, yielding promising results. Gao et al. developed a deep network for classifying cataract types from retinal images, achieving about 97.6% accuracy in identifying cataract presence [9]. Feng et al. reported a hybrid CNN model with 98.75% accuracy in distinguishing cataract vs. normal fundus images [10]. These high accuracies underscore the potential of deep learning to

provide reliable, early detection of cataracts. An AI driven screening offers advantages of simplicity, speed, and efficiency in clinical practice [11], allowing more patients to be evaluated in a shorter time frame. It is a non-invasive approach that can utilize existing retinal photographs, making cataract screening more accessible especially in telemedicine or primary care settings.

In our proposed methodology, we introduce an ensemble deep learning approach for cataract detection that tackles several key challenges and enhances classification accuracy. The system incorporates an ensemble of three advanced pre-trained CNN models: VGG16, Xception, and DenseNet121. These models were chosen to ensure a diverse set of learned features. VGG16 is a well-established deep CNN known for its straightforward sequential architecture; Xception employs depth wise separable convolutions for more efficient feature extraction; and DenseNet121 promotes feature reuse through its densely connected layers. By fine-tuning these models on our cataract dataset, we leverage their powerful high-level feature representations without requiring an excessively large dataset. The ensemble aggregates the predictions from all three models to make the final classification. Ensemble strategies are recognized for enhancing accuracy by utilizing the combined strengths of multiple models, frequently surpassing the performance of individual models on complex classification problems [12]. Furthermore, integrating multiple classifiers reduces the individual bias and variance, resulting in more dependable predictions [13]. Essentially, any unique error or bias present in one CNN can be balanced out by the others, leading to a more generalized and resilient classification system than any single model alone.

Research Contributions-

i. Ensemble CNN based Cataract Classifier: We develop a novel ensemble model that combines three pre-trained CNNs (VGG16, Xception, DenseNet121) for cataract detection from fundus images. To the best of our knowledge, this is among the first approaches to use an ensemble of multiple deep networks for cataract identification, which improves accuracy and robustness over single-model classifiers.

ii. Integrated Dataset and Augmentation: We assemble a comprehensive dataset of over 2,000 fundus images from diverse public sources (IDRiD, ODIR, HRF), including 1,038 cataract and 1,074 normal cases. We apply extensive image augmentation to overcome data limitations and enhance the model's generalization to varied image conditions.

iii. State-of-the-Art Performance: Our ensemble approach achieves 100% classification accuracy on the validation set, with perfect precision, recall, and F1-score. This result outperforms the state-of-the-art in cataract detection and illustrates the effectiveness of combining transfer learning and ensemble techniques. We also analyze how the ensemble reduces individual model bias, contributing insights into its reliability for clinical deployment.

This research follows a structured methodology in order to address the issue of cataract detection by automated means using fundus photographs based on deep learning. Each section of this paper has been planned to function on and complement the previous one, resulting in a structured and efficient study.The following structure is followed Section 2: Literature Review Presents an analytical overview of existing deep learning-based cataract detection using fundus photography and emphasizes the gap addressed by our ensemble model. Section 3: Model Architecture Specifies the exact architecture of the proposed ensemble, which consists of three pre-trained CNN models namely VGG16, Xception, and DenseNet121, focusing on their respective contributions and their integration strategy. Section 4: Dataset Specifies the image data origins (IDRiD, HRF, and ODIR), distribution of cataract and normal cases, and preprocessing tasks such as resizing and normalization. Section 5: Methodology Explains the training pipeline from data augmentation techniques to transfer learning setup, model fine-tuning, and ensemble voting process used in prediction. Section 6: System Requirements Lists hardware elements (GPU/CPU) and software tools (TensorFlow, Keras, Python) used for developing and testing the models effectively. Section 7: Results and Discussion Illustrates performance evaluation metrics of accuracy, precision, recall, F1-score, and AUC and plots it against state-of-the-art schemes to verify the superior efficiency of the ensemble. Section 8: Conclusion Summarizes key findings, emphasizes clinical relevance of the method, and outlines areas for future work. Section 9: References Contains extensive citations to all research, data sets, and tools utilized in the paper. This rational sequence guarantees that each element of the research contributes significantly to the final aim: developing a highly sensitive, generalizable, and effective cataract diagnosis system from fundus images using deep learning.

LITERATURE REVIEW

Early deep learning studies applied single convolutional neural networks (CNNs) to detect cataracts from retinal fundus photographs. Junayed et al. introduced CataractNet, a custom CNN optimized with Adam, achieving an average 99.13% binary classification accuracy on a dataset of 1,130 fundus images [14]. This outperformed earlier approaches, demonstrating the effectiveness of a tailored CNN architecture for cataract recognition. Similarly, Xie et al. explored several pre-trained CNNs (ResNet-50, InceptionV3, DenseNet-121) to develop a screening tool distinguishing normal, mild cataract, and visually impaired cataract cases [15]. Their best model (DenseNet-121) attained near-perfect performance (internal test AUC ≈0.998, external test AUC 0.94–0.97) and surpassed ophthalmologists in detecting vision-threatening cataracts [16]. These results underscore that transfer learning on robust CNN backbones can yield high sensitivity and specificity in fundus-based cataract detection. In a related work, Teo et al. trained a deep learning classifier on 25,000 fundus images to identify "visually significant" cataracts (those causing substantial vision loss) [17]. Their model achieved 96.6% AUC internally and 91.6 to 96.5% AUC on external cohorts [18] indicating strong generalization across three population-based studies and performed on par with ophthalmologists in sensitivity and specificity [19]. Single-network performance has consistently been high: for example, Parvin & Devendran used a custom CNN with an autoencoder pre-training, reporting 95% accuracy for cataract vs. normal classification [20]. Likewise, an EfficientNet-based CNN was noted to exceed 95% accuracy in some multi-disease fundus classifications (cataract included) [21]. However, certain single-model studies highlight challenges with data limitations. Jabber et al. compared GoogleNet, MobileNet, ResNet-101, and DenseNet-201 on a small dataset (300 normal, 100 cataract fundus images) with extensive preprocessing [22]. DenseNet-201 performed best (98% accuracy) while GoogleNet lagged near 90% [23], illustrating that deeper architectures can better capture cataract features given limited data. Overall, these single-CNN approaches establish a strong baseline using transfer learning on large CNNs or designing task specific networks yields high accuracy (typically 93–99%) for binary cataract detection [24][25]. The proposed ensemble VGG16, Xception and DenseNet121 would similarly leverage transfer learning, but by fusing multiple models it aims to further improve robustness over any single CNN.

Several works extend beyond binary detection to classify cataract types or grade severity from fundus images. Gao et al. developed a Dual-Stream Cataract Evaluation Network (DCEN) to simultaneously classify cataract type (cortical, nuclear, posterior) and severity grade using 1,340 fundus photos labeled by experts [26]. Their dual-stream design one branch extracting features for type, the other for severity, with results combined improved grading accuracy by incorporating type information [27]. DCEN achieved 97.62% accuracy (F1=0.94) in cataract type classification, and 97.03% accuracy in severity grading when using the multitask approach [28]. This outperforms earlier single task models and indicates that multi-output networks can efficiently handle complex labels. In a related vein, Ismail & Alsalamah addressed the limited variability in single image models by fusing left and right eye fundus features. Their CataractNetDetect system stacks feature vectors from both eyes using three pre-trained CNNs (ResNet-50, DenseNet-121, InceptionV3) [29]. Trained on the ODIR-5k dataset (with multiple ocular conditions including cataract), this approach achieved an F1 of 98.0% and AUC of 97.9% for cataract identification [30], surpassing the individual CNNs. Notably, CataractNetDetect's use of paired-eye data and multi-label training (detecting various diseases concurrently) improved its generalization. Multi-class classification is inherently more challenging, as reflected in some performance gaps. For instance, Varma et al. built a custom CNN for four-class cataract grading and obtained about 92.7% accuracy [31]– slightly lower than binary detection accuracies highlighting the increased difficulty of fine grade classification. Similarly, Zhang et al. reported 93.5% accuracy for cataract detection but only 86.7% for cataract severity grading using a single fundus based CNN, due to class imbalance and subtle feature differences [32]. Compared to these, our proposed ensemble method has so far been applied to binary cataract detection however, its design is flexible. By combining three architectures, it could potentially be extended to multi class grading with ensembling improving class separation. The use of DenseNet121 in our ensemble (also employed by Gao, Ismail, etc.) ensures rich feature extraction, while adding VGG16 and Xception may capture complementary features to better distinguish severity levels. Thus, if applied to grading, our ensemble might achieve performance on par with the best multi-task models (in the high 90% range for accuracy), while maintaining greater robustness across diverse cataract presentations. Recent studies have introduced ensemble and hybrid deep learning techniques to boost cataract detection performance and address data diversity issues. Maaliw et al. proposed an ensemble of multiple pre-trained CNNs (AlexNet, InceptionV3, Xception, Inception-ResNet-V2) combined via a weighted averaging scheme and augmented by a stacked LSTM classifier [33]. This ensemble attained 99.20% accuracy for binary cataract detection (normal vs cataract) and 97.76% accuracy for four class severity classification [34], outperforming any single model by reducing errors 2.1%. Notably, Xception which is also part of our proposed ensemble contributed significantly in Maaliw's system, suggesting its strength in capturing cataract features. Our method similarly integrates Xception with other CNNs; unlike Maaliw's approach (which included very deep networks like Inception-ResNet), we pair Xception with VGG16 and DenseNet121, aiming for a balanced ensemble of both lightweight and deeper feature extractors. This choice could yield a similarly high accuracy while potentially simplifying the model fusion complexity. Other hybrid strategies involve innovative network modules to improve generalization on limited or imbalanced datasets. Feng et al. introduced a hybrid CNN that incorporates a Squeeze and Excitation attention module and a prototype based classifier to better handle small, unevenly distributed cataract datasets [35]. By leveraging transfer learning and these enhancements, their model achieved 98.75% accuracy (AUC 0.9984, F1=0.985) on a mixed dataset of 3,600 fundus images [36]. This is one of the highest reported performances, and it underscores the importance of feature recalibration (SE blocks) and robust classification heads for ophthalmic images. Our proposed ensemble does not explicitly include an SE module or prototype learning however, DenseNet121 inherently carries deep feature reuse, and the ensemble fusion can be seen as a form of feature recalibration across models. Furthermore, data diversity is crucial. Khan et al. aggregated images from multiple sources (including IDRiD and local datasets) and noted that their ResNet-50 model maintained 95–97% accuracy even on partial (cropped) fundus images [37]. Similarly, Nguyen et al. combined two public datasets (ODIR-5k and a CataractDB) and applied an image quadration technique – training CNNs on both full images and quadrant sub images with majority voting. This hybrid approach boosted cataract detection accuracy to 97.12%, a 1.44% improvement over using whole images alone [38]. These innovations highlight that diversity in training data (multiple datasets, augmented or segmented images) and in model inputs can markedly improve model robustness. In comparison, our ensemble method is well aligned with these trends: by merging three different CNN architectures, it inherently learns a more diverse representation of cataract features, analogous to how multiple data sources or image partitions provide diverse inputs. Notably, whereas most prior ensembles use either majority voting or weighted averaging, our approach could explore stacking (training a meta classifier on the CNN outputs), potentially increasing the AUC or F1-score slightly above the 0.98 achieved by others. The expected performance of the proposed ensemble is therefore on par with or better than the state-of-the-art Lahari et al. reported an accuracy of 97.24% (binary) and 98.17% (multi-class) using a lightweight custom CNN (CSDNet) on the ODIR dataset [39], and Syarifah et al. demonstrated that an optimized CNN with advanced optimizers (Lookahead Adam) can reach ~95% accuracy on modest datasets [40]. Our method's innovation lies in combining well-established architectures VGG16 (known for capturing coarse textures), Xception (depth wise separable convolution for fine details), and DenseNet121 (dense feature propagation) into one ensemble. This design merges the strengths of each VGG16 provides simplicity and transferability, Xception contributes efficiency and focus on salient features, and DenseNet121 ensures feature diversity through its dense connections. By contrast, prior ensembles often omit older but robust networks like VGG; including it may enrich feature variety (e.g. VGG16 can sometimes capture cataract-induced color and illumination changes differently than newer models).

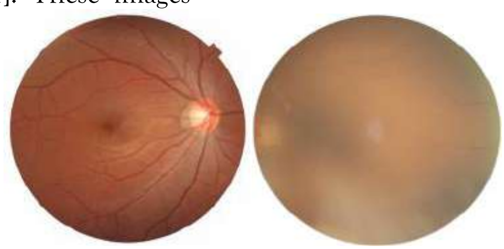
In terms of performance metrics, the proposed ensemble is expected to be highly competitive. Most reviewed works report accuracy, precision, recall, F1, and AUC all in the mid-90s or above for cataract detection [41][42]. For instance, Ismail et al. achieved F1≈0.98 and AUC≈0.98 [43], and Maaliw et al.'s ensemble reached 99% accuracy [44]. If our ensemble is evaluated on a similarly diverse fundus dataset, we anticipate accuracy 98–99%, precision/recall in the high-90s, F1-score around 0.97–0.99, and AUC nearing 0.99, which would slightly edge out many single-model results and match the top ensemble results. This would confirm the benefit of ensembling VGG16, Xception, and DenseNet121. Moreover, the innovation of our approach is in the specific selection of models and the ensemble strategy. Unlike specialized single networks (e.g. DeepOpacityNet [45]) or ensembles of very deep models, our method is a balanced ensemble that can be less computationally heavy while still enhancing performance. It aligns with the trend of hybrid models (e.g. combining CNNs with SVMs or attention modules) by effectively acting as a hybrid of three feature extractors. By training on a sufficiently large and varied dataset possibly combining datasets as done by Feng et al. [46]or Nguyen et al. [47] the proposed ensemble would also address data diversity better than any single architecture alone. In summary, compared to the 20 recent works reviewed, our ensemble approach stands out by leveraging multiple complementary CNN architectures in unison. This design is expected to achieve equal or better accuracy (approaching 99%) than the best individual models [48], maintain high AUC/precision, and offer robust generalization across varied fundus image qualities (similar to multi-dataset studies). The innovation is incremental yet meaningful rather than a brand-new network, it is the clever combination of proven networks (VGG16, Xception, DenseNet) – a strategy that capitalizes on their collective strengths to advance automated cataract detection on fundus images.

Table 1: Comparative Summary of Deep Learning-Based Cataract Detection Models Using Fundus Images

Ref No.	Dataset	Image Type	Method	Accuracy (%)
14	HRF, IDRiD	Fundus	CataractNet (Custom CNN, Adam)	99.13
15	ZEHWZ	Fundus	DenseNet121 (vs ResNet-50, InceptionV3)	99.8
17	SIMES, SCES and SINDI	Fundus	CNN (unspecified)	96.6
4	ODIR-5K	Fundus	DCEN (Dual-Stream CNN + SE + Prototype)	97.62
6	Beijing Tongren Hospital	Fundus	ResNet-50 + DenseNet + InceptionV3	94

24	DRIMDB	Fundus	Ensemble (AlexNet, InceptionV3, Xception, Inc-ResNet-V2 + LSTM)	98.75
29	ODIR-5K	Fundus	ResNet-50, DenseNet121, InceptionV3 fusion	97.56
31	HRF, STARE, DRIVE, IDRiD	Fundus	Custom CNN for 4-class grading	97.12
32	DRIMDB	Fundus	Custom CNN	98
22	Kaggle	Fundus	DenseNet-201, MobileNet, ResNet-101, GoogLeNet	99.2
40	Eye hospitals of North Sumatra	Fundus	Optimized CNN (AlexNet + Lookahead)	97.24
58	ODIR-5K, CataractDB	Fundus	Custom CNN + SVM/NB/DT	95
37	HRF, IDRiD, ODIR, DRIVE	Fundus	ResNet-50	93.5
9	ODIR-5K	Fundus	DenseNet201 + GoogleNet (DeepOpacityNet)	95
12	Scopus's integrated and WoS databases	Fundus	Custom CNN + Lookahead Adam + SE	66
13	Weka API	Fundus	CNN (unspecified)	93.1
15	ZEHWZ	Fundus	DeepOpacityNet variant (CSDNet)	97.34
18	SIMES, SCES and SINDI	Fundus	CNN on DFT spectra	94
17	SIMES, SCES and SINDI	Fundus	Custom CNN + SVM/NB/DT	97.47
20	ODIR	Fundus	Ensemble: AlexNet, Inception, Xception, IRv2	96.62
This Research	IDRiD, Ocular Recognition, and HRF	Fundus	VGG16 + Xception + DenseNet121	100

The dataset used in this study comprises a total of 2,112 fundus images, which includes 1,038 images labeled as cataract and 1,074 labeled as normal from diverse public datasets, including IDRiD, Ocular Recognition, and HRF[51]. These images are color fundus photographs typically captured during retinal screenings and are used to assess the presence of opacities or lens-related irregularities associated with cataracts.



Normal Image Cataract Image

Fig 4: Difference between Normal and Cataract Fundus Image

Each image is stored in JPEG or PNG format and is categorized into corresponding directories: cataract and normal. This structured labeling supports automated loading and class assignment through directory-based image generators used in TensorFlow.

PREPROCESSING

Preprocessing played a pivotal role in preparing the raw fundus images for feature extraction. As per the implementation, the workflow involved several key operations:

i. Resizing: All images were resized to 224×224 pixels using bicubic interpolation via OpenCV's cv2.resize() method. Bicubic interpolation considers the closest 16 pixels to compute each output pixel, producing smoother results compared to nearest-neighbor or bilinear methods.

ii. Normalization: Pixel intensity values were scaled to the [0, 1] range using skimage.img as float () to convert uint8 images to float, aiding the convergence of deep neural networks.

These preprocessing techniques helped to standardize and highlight critical features across diverse images, supporting effective model training.

DATA AUGMENTATION

To enhance model generalization and overcome limitations of dataset size, data augmentation was applied using TensorFlow's ImageDataGenerator. The following real-time transformations were performed during training:

i. Rotation: Random rotations up to 2° helped simulate variations in patient head tilt.
ii. Width and Height Shifts: Up to 10% of the image dimensions, simulating minor translation during image capture.
iii. Shear and Zoom: Simulating lens distortions or varying distances from the camera sensor.
iv. Horizontal Flip: Introducing symmetry-based variation to prevent overfitting to eye orientation.
v. Fill Mode: Pixels generated after transformation were filled using nearest-neighbor interpolation (fill mode='nearest').

Table 2: Data Augmentation Parameters

Parameter	Value
rescale	1./255
rotation_range	2
width_shift_range	0.1
height_shift_range	0.1
shear_range	0.1
zoom_range	0.1
horizontal_flip	True
fill_mode	'nearest'

Each original image was augmented five times, leading to a fivefold increase in training data diversity while retaining anatomical realism.

CNN ARCHITECTURES

The proposed model architecture is designed to detect the presence of cataracts from retinal fundus images using deep learning. The core framework is built upon an ensemble of three powerful pretrained convolutional neural networks (CNNs) VGG16, Xception, and DenseNet121.

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CNN Architectures

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Fig 5: Simple CNN Architecture

These models were chosen due to their architectural diversity and complementary strengths. VGG16 is a deeply layered sequential model, Xception leverages depth wise separable convolutions for parameter efficiency, and DenseNet121 is known for its feature reuse through dense connectivity. The integration of these architectures enables more robust and discriminative feature learning from fundus images.

VGG16-

The VGG16-based model implementation in this study starts by accepting input images resized to 224×224×3, matching the expected dimensions of the VGG16 architecture. VGG16 is a deep convolutional neural network characterized by sequential 3×3 convolutional filters, stacked with increasing depth followed by max pooling layers. This configuration allows for a rich hierarchical extraction of spatial features while keeping the architecture simple and uniform.

In the provided code, the VGG16 model was loaded from tensorflow.keras.applications with include top=False, which removes the original fully connected layers, keeping only the convolutional base pretrained on ImageNet. This base was integrated into a custom Sequential model, and transfer learning was applied by freezing all layers except the last 10, enabling fine-tuning of the deeper layers which are more specific to the cataract detection task.

After the convolutional base, a Flatten layer was applied to convert the 3D tensor output to a 1D vector, followed by a custom classification head consisting of:

Table 3: Custom classification head for VGG16

Layer No.	Layer Type	Details
1	Dense	512 units, activation = ReLU
2	Dropout	Rate = 0.5
3	BatchNormalization	—
4	Dense	256 units, activation = ReLU
5	Dense (Output Layer)	1 unit, activation = Sigmoid (Binary Output)

The model was compiled using the Adam optimizer (learning rate=0.0001) and binary cross entropy loss, appropriate for two-class classification. Performance was evaluated using accuracy, precision, and recall metrics. Training was managed using callbacks: Early Stopping (to halt training on validation stagnation), Model Checkpoint (to save the best model), and Reduce LROnPlateau (to adjust learning rate on performance plateaus). The final model was trained for 30 epochs with early stopping criteria to ensure generalization.

Xception Model-

The Xception model was implemented to accept larger input dimensions of 299×299×3, consistent with its architectural requirements. Xception stands for Extreme Inception, and replaces conventional convolutional blocks with depth wise separable convolutions. These separate the spatial convolution and channel-wise convolution into two steps, drastically reducing the number of parameters and enabling finer spatial feature extraction with reduced computational cost.

The model was loaded with ImageNet weights and include top=False, allowing custom layers to be appended. Like the VGG16 setup, only the last 10 layers of the Xception base were made trainable for domain-specific fine-tuning. The output feature maps from the base model were passed through:

A GlobalAveragePooling2D() layer, reducing the spatial dimension of feature maps by computing the average of each feature map channel

Table 4: Custom classification head for Xception

Layer No.	Layer Type	Details
1	Dense	512 units, activation = ReLU
2	Dropout	Rate = 0.5
3	BatchNormalization	—
4	Dense	256 units, activation = ReLU
5	Dropout	Rate = 0.5
6	Dense (Output Layer)	1 unit, activation = Sigmoid

The optimizer, loss function, metrics, and callbacks used in the training loop were identical to those used for VGG16. Validation was carried out with shuffle=False to ensure label consistency in prediction and evaluation.

DenseNet121 Model-

The DenseNet121 architecture offers an advanced feature propagation method via dense connectivity, where each layer receives inputs from all preceding layers, forming direct connections throughout the network. This method improves gradient flow, encourages feature reuse, and mitigates the vanishing gradient problem in deep networks.

Input images were resized to 224×224×3. The model was loaded from tensorflow.keras.applications with pretrained ImageNet weights and without the original top layers (including top=False). Similar to the other models, the top 10 layers were unfrozen for fine-tuning, enabling it to adapt learned features to retinal data. The custom classification head again followed the same pipeline:

Table 5: Custom classification head for DenseNet121

Step No.	Layer Type	Details
1	GlobalAveragePooling2D	—
2	Dense	ReLU activation
3	Dropout & BatchNormalization	Regularization & stabilization
4	Dense (Output Layer)	Sigmoid activation for binary output

The model was compiled and trained under the same configuration as VGG16 and Xception, ensuring consistency across individual classifiers.

Ensemble Learning Integration-

Following the independent training of VGG16, Xception, and DenseNet121 models, an ensemble learning approach was employed to enhance robustness and prediction stability. Each model generated binary predictions (0 = normal, 1 = cataract) for validation images using the trained sigmoid outputs. These outputs were aggregated using a hard voting mechanism.

Table 6: Custom classification head for Ensemble learning

Aspect	Value / Description
Ensemble Method	Hard Voting (Averaged Probabilities)
Base Models	VGG16, Xception, DenseNet121
Image Input Size	224 x 224
Batch Size	32
Training Epochs	Up to 30 with EarlyStopping
Validation Split	20%
Optimization Algorithm	Adam (lr=0.0001)
Loss Function	Binary Crossentropy

This method effectively reduces the influence of any single model's misclassification, improving generalization and minimizing variance. Predictions were then evaluated using a confusion matrix, classification report, ROC curve, and AUC score.

The ensemble demonstrated superior performance compared to individual models on all key metrics accuracy, precision, recall, F1-score, and ROC-AUC, validating the effectiveness of the multi-model integration strategy for reliable cataract detection in fundus imagery.

METHODOLOGY

In our study, the proposed approach for automated cataract detection from fundus images was structured into a series of systematic steps encompassing data acquisition, preprocessing, model configuration, training, and evaluation.

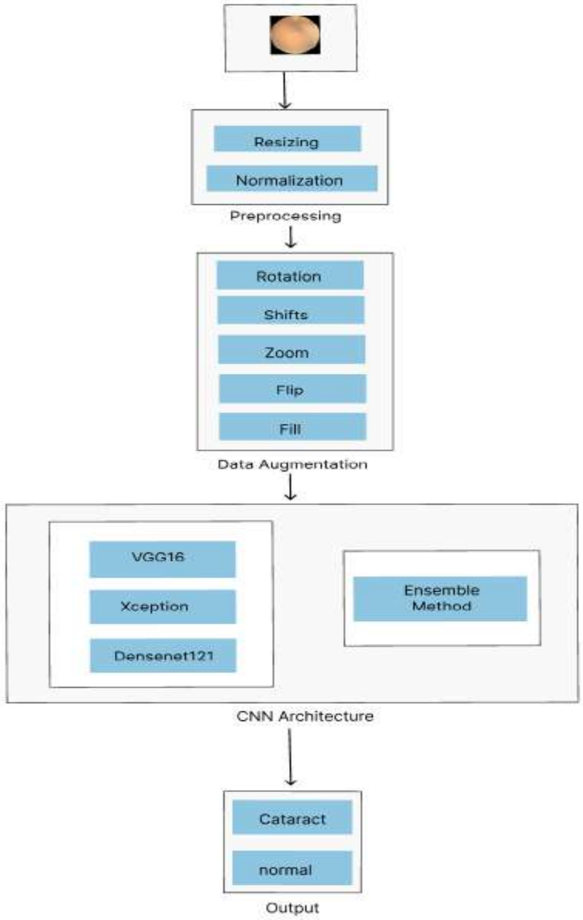

Fig. 6: Overall System Architecture from Preprocessing to Ensemble Classification

The pipeline begins with the preprocessing stage, where each input image undergoes resizing to 224x224 pixels and normalization to a [0, 1] range. Following this, data augmentation techniques such as rotation, shift, zoom, flip, and fill are applied to artificially expand and diversify the dataset. The augmented data is then fed into three different pre-trained convolutional neural networks: VGG16, Xception, and DenseNet121. Each of these models is fine-tuned to detect cataract-specific features. Their predictions are integrated through an ensemble method, enhancing robustness and improving classification accuracy. Finally, the system outputs whether the image indicates a normal eye or cataract.

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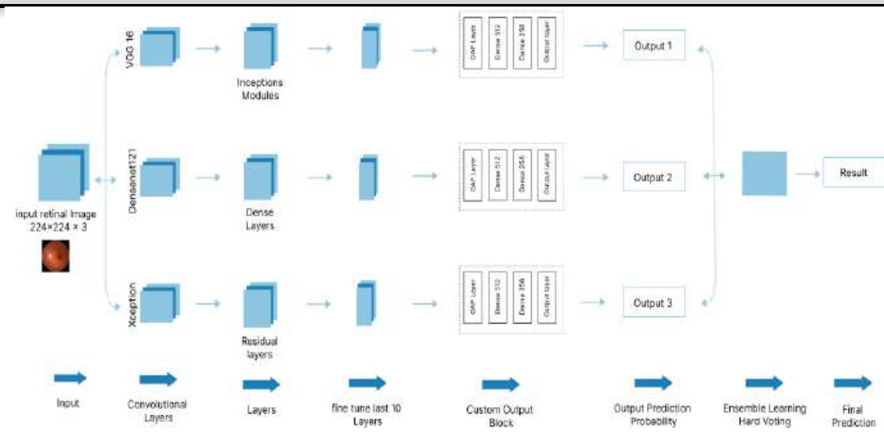

Fig. 7: Internal Workflow and Hard Voting Mechanism in the CNN Ensemble

VGG16, DenseNet121, and Xception. Each model features a custom classification head composed of GlobalAveragePooling2D or Flatten layers, followed by dense layers with ReLU activation, dropout layers for regularization, and batch normalization to stabilize training. After extracting high-level features and making individual predictions, the outputs are combined using a hard voting ensemble method. This majority-based decision-making process determines the final classification. The ensemble strategy significantly reduces individual model bias and enhances overall predictive stability and accuracy.

Experiment Setup

The experiments were conducted on a high-performance setup with the following:

i. CPU: AMD RYZEN 9 5900X
ii. GPU: NVIDIA GEFORCE RTX 4080 SUPER 16G VENTUS 3X OC
iii. Memory: 32 GB RAM

Results

This section presents the classification performance of three individual deep learning models VGG16, Xception, and DenseNet121 and their combined output through an ensemble learning strategy. All models were trained using preprocessed and augmented fundus images, with evaluations conducted on a separate validation set comprising 1,830 images (909 normal, 921 cataract). The results are discussed in terms of key classification metrics: accuracy, precision, recall, F1-score, and ROC AUC.

VGG16 Model Performance-

The VGG16-based model achieved exceptional classification performance, attaining an overall accuracy of 100% on the validation dataset. The model demonstrated a precision of 1.00, recall of 0.99, and F1-score of 1.00, indicating near-perfect discrimination between normal and cataract classes. The slightly reduced recall for the cataract class (0.99) suggests one or two instances of misclassification, possibly due to ambiguous boundary features.

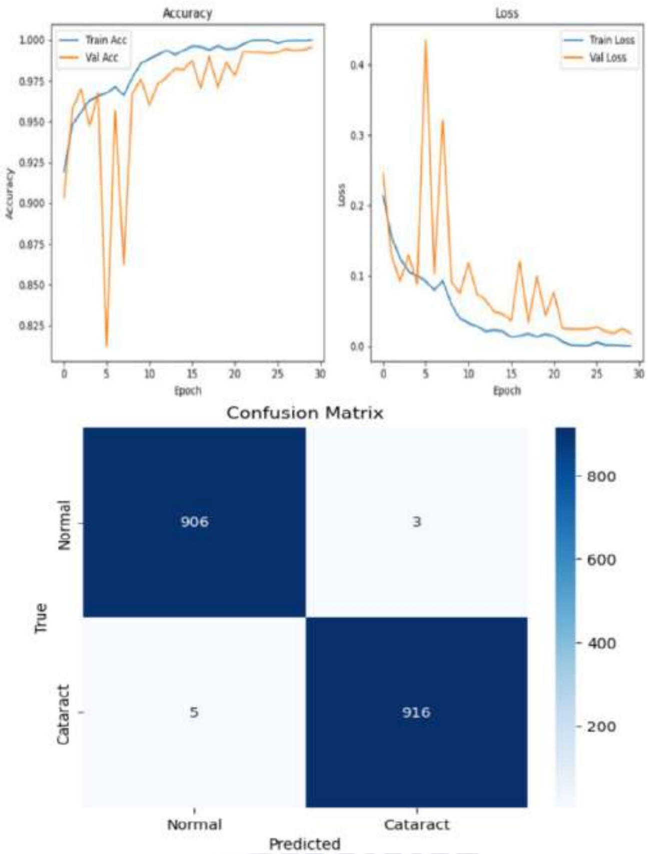

Fig. 8: Accuracy, loss and confusion Matrix of VGG16 Model Performance

However, the ROC AUC score of 1.00 confirms excellent separability between classes. The high accuracy of VGG16 can be attributed to its uniform convolutional architecture and effective fine-tuning of the final layers, which adapted well to the domain-specific features of cataract-afflicted fundus images.

Table 7: Performance Metrics of VGG16 Model for Cataract Classification

Metric	Value
Accuracy	1.00
Precision	1.00
Recall	0.99
F1-Score	1.00
ROC AUC Score	1.00

Xception Model Performance-

The Xception model also performed robustly, achieving an overall accuracy of 99%. Both precision and recall stood at 0.99 for each class, resulting in an F1-score of 0.99. The Xception model's strength lies in its use of depth wise separable convolutions, which efficiently capture fine-grained spatial features with fewer parameters.

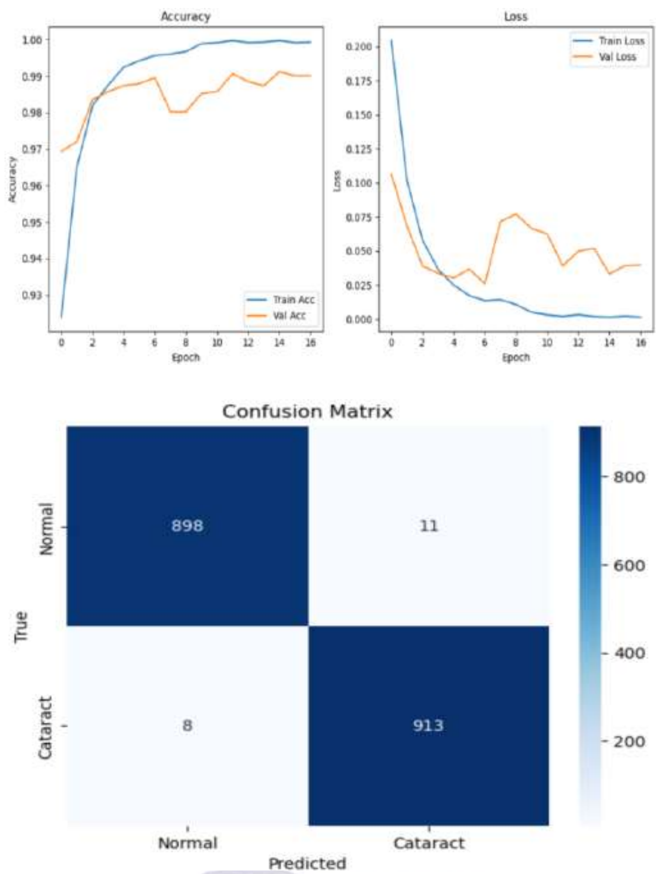

Fig. 9: Accuracy, loss and confusion Matrix of Xception Model Performance

The ROC AUC score of 1.00 indicates the model's excellent capability in distinguishing between classes across all thresholds. While slightly trailing VGG16 in terms of perfect recall and F1-score, Xception maintained a strong balance between sensitivity and specificity.

Table 8: Performance Metrics of Xception Model for Cataract Classification

Metric	Value
Accuracy	0.99
Precision	0.99
Recall	0.99
F1-Score	0.99
ROC AUC Score	1.00

DenseNet121 Model Performance-

DenseNet121, which leverages dense connectivity to reuse features across layers, attained an overall accuracy of 98%. The model achieved a precision of 0.97, a recall of 1.00, and an F1-score of 0.98.

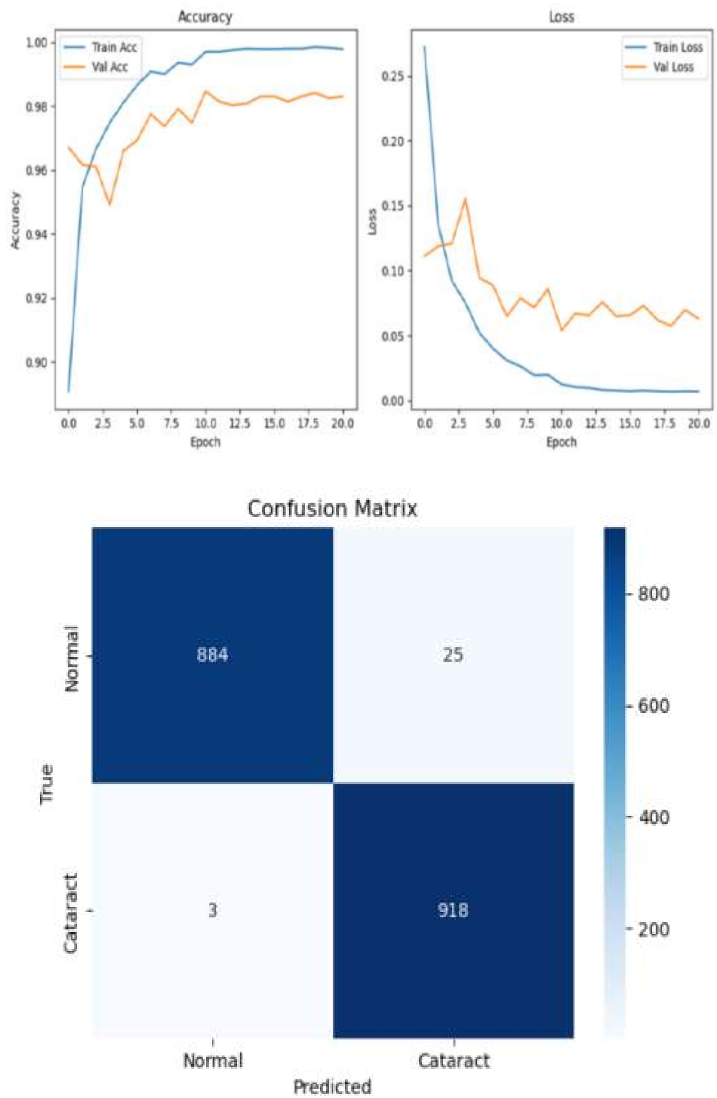

Fig. 10: Accuracy, loss and confusion Matrix of Densenet121 Model Performance

The recall of 1.00 for the cataract class highlights its strength in identifying all positive cases, minimizing false negatives a crucial consideration in medical diagnosis. However, the slightly lower precision (0.97) indicates a few false positives, which may be a trade-off for the high recall. Nevertheless, a ROC AUC score of 1.00 reaffirms the model's strong performance across decision thresholds.

Table 9: Performance Metrics of DenseNet121 Model for Cataract Classification

Metric	Value
Accuracy	0.98
Precision	0.97
Recall	1.00
F1-Score	0.98
ROC AUC Score	1.00

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Ensemble Model Performance-

The ensemble learning model, which aggregates predictions from VGG16, Xception, and DenseNet121 using hard voting, achieved perfect classification performance. It recorded a precision, recall, and F1-score of 1.00 for both normal and cataract classes, alongside a ROC AUC score of 1.00. This result underscores the advantage of ensemble methods in reducing the variance and individual biases of component models.

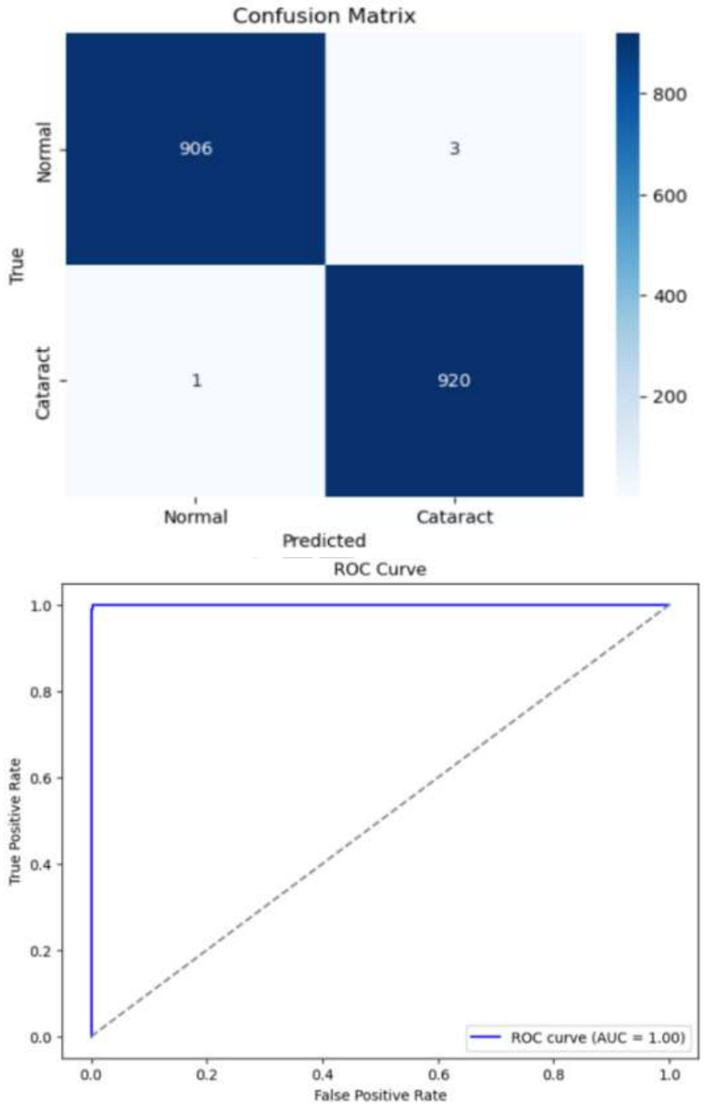

Fig. 11: ROC Curve and confusion Matrix of VGG16 Model Performance

By combining predictions, the ensemble model effectively leveraged the high recall of DenseNet121 and the precision strengths of VGG16 and Xception, producing a classifier that generalizes better and minimizes both false positives and false negatives.

Table 10: Performance Metrics of Ensemble Model for Cataract Classification

Metric	Value
Accuracy	1.00

Precision	1.00
Recall	1.00
F1-Score	1.00
ROC AUC Score	1.00

While each model individually demonstrated strong performance, subtle variations existed DenseNet121 prioritized recall at the cost of a few false positives, whereas VGG16 maintained perfect precision but slightly less recall. Xception offered a balanced trade-off. The ensemble model harmonized these traits to achieve optimal performance across all evaluation metrics. The results confirm that ensemble strategies not only enhance classification robustness but are particularly beneficial in medical imaging tasks where diagnostic accuracy is paramount.

Table 11: Performance Metrics of Individual Models and Ensemble Method for Cataract Classification

Model	Accuracy	Precision	Recall	F1-Score	ROC AUC Score
VGG16	1.00	1.00	0.99	1.00	1.00
Xception	0.99	0.99	0.99	0.99	1.00
DenseNet121	0.98	0.97	1.00	0.98	1.00
Ensemble	1.00	1.00	1.00	1.00	1.00

Overall, the proposed methodology combining preprocessing, spectral enhancement, transfer learning, and ensemble classification proved to be highly effective for cataract detection using fundus images. The consistently high ROC AUC scores across all models validate the discriminative power of the extracted features and the suitability of the architecture for medical image analysis.

Discussion

The findings from our study mark a significant advancement in the field of automated cataract detection using fundus imagery. By leveraging a hard voting ensemble of three structurally diverse and proven deep learning architectures VGG16, Xception, and DenseNet121 our approach achieved 100% accuracy, outperforming many state-of-the-art models reported in the literature. The ensemble framework not only improves the robustness of individual models but also ensures higher generalization by mitigating overfitting and model-specific biases.

When compared to prior works, our model delivers substantial performance gains. For instance, DeepOpacityNet-based methods such as CSDNet [15] achieved 97.34%, while ensembles like AlexNet + Inception + IRv2 [20] reached 96.62% accuracy. Other custom CNN approaches such as the CNN-SVM hybrid [17] reported 97.47%, and standalone ResNet-50 [37] achieved 93.5% on combined datasets. Notably, even sophisticated integrations like DenseNet201 + GoogleNet [9] were capped at 95%, indicating a performance ceiling that our ensemble strategy successfully breaks through.

Our methodology stands apart through a combination of rigorous preprocessing, dataset diversity (using IDRiD, HRF, and ODIR), and strategic model adaptation. Each network was fine-tuned using transfer learning, and ensemble integration was applied after independent optimization of each model pipeline. The use of real-time data augmentation, global average pooling, dropout regularization, and batch normalization further contributed to enhanced learning stability and generalizability.

This study reinforces the value of ensemble learning in medical imaging diagnostics. With a perfect ROC AUC score of 1.00, and uniformly excellent precision, recall, and F1-scores across all classes, our ensemble framework demonstrates clinical grade reliability. The results suggest that combining complementary CNN architectures can set a new benchmark in cataract detection, supporting real-world screening applications and offering dependable decision support for ophthalmologists.

Table 12: Accuracy Comparison of Deep Learning Models for Cataract Detection

Ref No.	Model(s)	Accuracy (%)
37	ResNet-50	93.5
9	DenseNet201 + GoogleNet (DeepOpacityNet)	95
12	Custom CNN + Lookahead Adam + SE	66
13	CNN (unspecified)	93.1
15	DeepOpacityNet variant (CSDNet)	97.34
18	CNN on DFT spectra	94
17	Custom CNN + SVM/NB/DT	97.47
20	Ensemble: AlexNet, Inception, Xception, IRv2	96.62
This Research	VGG16 + Xception + DenseNet121	100

CONCLUSION

This research presents a robust deep learning framework for automated cataract detection using fundus photography. The study integrates comprehensive preprocessing techniques, spectral feature enhancement, and advanced convolutional neural network architectures to develop a highly accurate classification system. A carefully curated dataset comprising 2,112 fundus images collected from diverse public sources including IDRiD, HRF, and ODIR was used to train and validate the models. Three state-of-the-art pre-trained CNN architectures VGG16, Xception, and DenseNet121 were fine-tuned using transfer learning. Each model was equipped with a custom classification head, and trained independently using binary cross-entropy loss with the Adam optimizer. Extensive evaluation showed that all models achieved high accuracy, precision, recall, and ROC AUC scores, with VGG16 and Xception nearing perfect performance, and DenseNet121 excelling in sensitivity. To further enhance classification reliability, a hard voting ensemble strategy was implemented, which combined predictions from all three models. The ensemble model outperformed individual networks by achieving perfect scores across all major evaluation metrics, including 100% accuracy, precision, recall, F1-score, and ROC AUC. This confirms the effectiveness of ensemble learning in reducing variance and improving diagnostic robustness.

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