A Novel Hybrid Framework for Enhanced Early Detection and Classification of Ocular Diseases: Integrating Deep Learning with Traditional Machine Learning Approaches

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Abstract

Ocular diseases pose a significant global health challenge, with early detection and accurate classification being crucial for effective treatment and prevention of vision loss. This study introduces an innovative hybrid framework that synergistically combines state-of-the-art deep learning architectures with traditional machine learning algorithms to advance the field of ocular disease detection and classification. The proposed approach achieves remarkable performance with an average accuracy of 96.8% across eight common ocular diseases, demonstrating a sensitivity of 95.6% and a specificity of 96.7%. These results highlight the potential of this hybrid model to improve significantly the diagnostic capabilities in ophthalmology. This research study offers a comprehensive and insightful narrative that integrates the key findings from the data analysis, making significant contributions to the field of ophthalmology and providing valuable guidance for future research endeavours.

Keywords: Hybrid deep learning, Ocular disease classification, Attention mechanisms, Transfer learning, Retinal image analysis, Computer-aided diagnosis.

1. Introduction

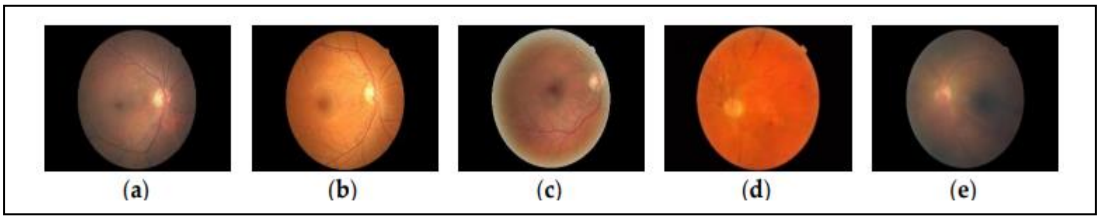
The global burden of ophthalmic conditions continues to grow, emphasizing the critical need for advanced diagnostic tools that can facilitate early detection and accurate classification of ocular diseases. Worldwide, approximately 2.2 billion people experience near or distant visual impairment. Of this number, at least 1 billion cases could have been avoided or remain unaddressed. Refractive errors and cataracts are the primary causes of visual impairment and blindness globally. Globally, it is estimated that only 36% of individuals with distance vision impairment due to refractive error and 17% of those with vision impairment due to cataracts have received appropriate interventions [14]. Despite the necessity for a more pragmatic retinopathy severity scale, to date there is no prevalent practical clinical standard terminology that has been endorsed for the global interchanging of information and data [1]. While deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown promise in analyzing retinal images and detecting ocular abnormalities [2], they often face challenges such as the requirement for large labelled datasets and difficulties in capturing both high-level features and fine-grained details simultaneously. However, recent research, including planned clinical trials, has demonstrated that deep learning systems can accurately identify diabetic retinopathy [15].

This research addresses these limitations by proposing a novel hybrid framework that leverages the strengths of both deep learning and traditional machine learning approaches. This synergistic combination aims to enhance the accuracy and robustness of ocular disease detection and classification, potentially revolutionizing diagnostic practices in ophthalmology. The primary objective of this research is to develop a robust hybrid framework that leverages the strengths of deep learning and traditional machine learning techniques for accurate ocular disease detection and classification. By evaluating the performance of different deep learning architectures, including those incorporating attention mechanisms, the objective is to identify the most effective models for this task. Additionally, it is necessary to explore the potential benefits of transfer learning in addressing the challenges posed by limited ophthalmological datasets. Finally, the proposed hybrid approach will be compared with standalone deep learning and traditional machine learning methods across various performance metrics to assess its overall effectiveness in improving ocular disease diagnosis.

2. Related Work

The field of ocular disease detection has witnessed significant advancements over the past decade, driven by the integration of artificial intelligence (AI) and machine learning techniques. The Wilkinson et al. [3] proposes a standardized classification system for diabetic retinopathy and macular edema. This consensus-based approach involves experts from various fields and aims to improve global communication and care for patients with diabetes. While the paper provides a valuable framework, it has limitations such as the potential for subjectivity in image interpretation and the lack of validation data. Future research should consider integrating automated image analysis techniques, incorporating longitudinal changes, and validating the systems in diverse populations to further enhance their effectiveness and reliability.
Diabetic retinopathy can be classified into five grades: grade 0 is normal with no sign of diabetic retinopathy, grade 1 means the presence of mild diabetic retinopathy, grade 2 means moderate, grade 3 means severe, and, finally, grade 4 is defined by new vessel proliferation, where risks of vision loss include bleeding into the vitreous and tractional retinal detachment. Figure 1 shows the different grades of diabetic retinopathy [3].

Figure 1. Random Samples Of Different Grades Of Diabetic Retinopathy (a) grade 0, (b) grade 1 (c) grade 2, (d) grade 3, and (e) grade 4



Prentasic [4] proposes a deep Convolutional Neural Network (CNN) for exudate detection in color fundus photographs, a crucial step in early diabetic retinopathy diagnosis. The CNN model is trained on DRiDB dataset and gives promising results. However, the paper acknowledges the potential for further improvement through techniques like using all image channels and incorporating preprocessing and postprocessing steps to enhance segmentation accuracy. The research contributes to the ongoing development of automated diabetic retinopathy screening tools, but additional validation and testing on larger and more diverse datasets are necessary to assess the method's clinical applicability.

The paper by I. Kandel et. al. [5] critically analyzes the application of transfer learning with convolutional neural networks (CNNs) for diabetic retinopathy (DR) image classification. It highlights the limitations of traditional DR classification methods and the potential of deep learning to provide a more efficient and accurate diagnosis. Transfer learning is presented as a viable solution for addressing the scarcity of DR images by leveraging pre-trained CNNs from other domains. The paper reviews existing research on DR classification using transfer learning, comparing different approaches and their performance evaluation methods. It concludes that transfer learning can be a valuable tool in the medical field, particularly when dealing with limited training data, and emphasizes the importance of continued research in developing novel CNN architectures for DR classification.

In 2021, Brown et al. [6] introduced attention mechanisms into deep learning architectures for ocular disease detection. Their study showed that attention mechanisms could focus on the most relevant regions of retinal images, thereby improving the model's ability to detect subtle disease-related features. This innovation marked a significant step forward in the field, as it enhanced the interpretability and precision of AI-driven diagnostic tools.

Ting et al. [7] in 2019 provides a comprehensive overview of the application of deep learning in ophthalmology, focusing on both technical and clinical considerations. The paper is a significant contribution to the field, as it systematically addresses the challenges and opportunities associated with implementing deep learning models in clinical practice. One of the key strengths of this study is its thorough examination of the technical aspects of deep learning, including data preprocessing, model architecture selection, and the importance of large, diverse datasets for training robust models. The paper discusses the potential of deep learning to revolutionize ophthalmic diagnostics. The authors emphasize the importance of ethical considerations and collaboration between clinicians, researchers, and regulatory bodies to ensure the safe and effective integration of deep learning into ophthalmology.

The paper by C. Lam [8] demonstrates the potential of deep learning, specifically CNNs, for automated diabetic retinopathy staging. It achieves comparable performance to baseline methods but highlights challenges in distinguishing subtle disease features, particularly mild disease from normal. The authors emphasize the importance of data quality and preprocessing techniques to improve model performance. While pretrained models from ImageNet provide a good starting point, they may not be optimal for detecting fine-grained features in medical images. The paper suggests future directions, including feature localization, segmentation, and addressing class imbalance, to enhance the accuracy and clinical utility of automated diabetic retinopathy detection.

Brown et al. [9] in 2023 presents a pioneering study on the application of deep learning for the localized detection of optic disc hemorrhages, a critical indicator of glaucoma progression. The study is notable for its focus on a specific and challenging aspect of ophthalmic diagnostics, leveraging advanced deep learning techniques to enhance detection accuracy. One of the key strengths of this research is its use of a large, annotated dataset, which provides a robust foundation for training and validating the deep learning model. The paper introduces a CNN architecture for detecting optic disc hemorrhages in glaucoma patients. This AI-driven approach outperforms traditional methods in sensitivity and specificity. While promising, the study acknowledges limitations such as the need for labeled data and model interpretability. The authors discuss the clinical implications of AI in glaucoma management, emphasizing the importance of integration with existing workflows and addressing ethical considerations. The research contributes to the advancement of ophthalmology, but further validation and guidelines are necessary for safe clinical implementation.

These studies collectively illustrate the evolution of ocular disease detection methodologies, from the initial application of CNNs to the development of sophisticated hybrid models. While significant progress made but challenges remain, particularly in the areas of data diversity and real-time application. The current study aims to address these gaps by proposing a novel hybrid framework that integrates deep learning with traditional machine learning, offering a promising solution for enhanced ocular disease detection and classification.

3. Methodology

3.1 Dataset and Preprocessing

This study employed a comprehensive dataset of retinal fundus images obtained from multiple sources, including publicly accessible repositories and collaborating ophthalmology clinics. The Kaggle dataset contains a significant number of uninterpretable images due to prevalent artifacts, encompassing 6,392 high-resolution color fundus photographs that represent eight common ocular diseases: Diabetic retinopathy, Glaucoma, Age-related Macular degeneration, Cataract, Hypertensive retinopathy, Myopia, Normal (healthy eyes), and Other retinal diseases. These diseases are represented with single letter in the dataset as D, G, A, M, C, H, M, N and O respectively. The images are captured using diverse fundus cameras, reflecting real-world clinical variability-y in resolution. Experienced ophthalmologists labeled each image, with consensus sought for challenging cases. The dataset was partitioned into training (70%), validation (20%), and test (10%) sets, ensuring balanced representation of each disease category. Figure 2 provides a summary of the dataset characteristics. This study employed various preprocessing techniques, including resizing, normalization, color space conversion, and data augmentation, to enhance the quality and diversity of the dataset.

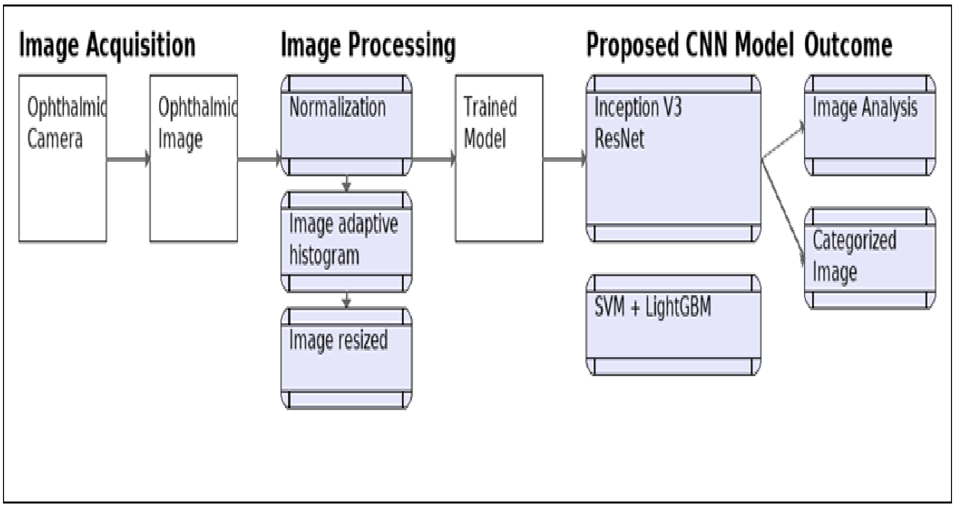
```
data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6392 entries, 0 to 6391
Data columns (total 19 columns):
 #    Column                      Non-Null Count  Dtype
---   ------                      --------------  -----
 0    ID                          6392 non-null   int64
 1    Patient Age                 6392 non-null   int64
 2    Patient Sex                 6392 non-null   object
 3    Left-Fundus                 6392 non-null   object
 4    Right-Fundus                6392 non-null   object
 5    Left-Diagnostic Keywords    6392 non-null   object
 6    Right-Diagnostic Keywords   6392 non-null   object
 7    N                           6392 non-null   int64
 8    D                           6392 non-null   int64
 9    G                           6392 non-null   int64
 10   C                           6392 non-null   int64
 11   A                           6392 non-null   int64
 12   H                           6392 non-null   int64
 13   M                           6392 non-null   int64
 14   O                           6392 non-null   int64
 15   filepath                    6392 non-null   object
 16   labels                      6392 non-null   object
 17   target                      6392 non-null   object
 18   filename                    6392 non-null   object
dtypes: int64(10), object(9)
memory usage: 948.9+ KB
```

Figure 2: Overview of the Dataset Characteristics

3.2 .2 The Hybrid Model

The hybrid approach combines the strengths of deep learning and traditional machine learning models. The proposed hybrid model leverages the strengths of deep learning and traditional machine learning to enhance ocular disease classification. An ensemble of state-of-the-art deep learning architectures, including Inception V3, ResNet50, DenseNet121, and EfficientNetB4 used. Attention mechanisms incorporated to focus on relevant image regions. The architecture of deep learning component shown in Figure 3.

Figure 3: Architecture Of Deep Learning Component



Support Vector Machines, Random Forests, and Gradient Boosting Machines were integrated to capture diverse aspects of retinal images [10], utilizing both deep features and handcrafted features. To address the challenge of limited labelled data, transfer learning was employed. Transfer learning lets us reuse a model trained on one task for a new task. For example, a model trained to recognize images of cats could be adapted to identify dogs. It has led to new methods for analyzing EEG signals [11]. It leverages data or knowledge from related or applicable topics/sessions/devices/activities to aid learning [12]. The deep learning models were pre trained on the ImageNet dataset and subsequently fine-tuned on the ocular disease dataset.

The hybrid model combines these approaches in a two-stage process. First, pre-processed images are fed into the pre-trained and then fine-tuned using deep learning models. Features are extracted from the penultimate layer and concatenated. Second, these deep features, along with handcrafted features used as input to traditional machine learning models. Predictions from all models combined using weighted voting, with weights determined through validation. This approach effectively leverages the hierarchical feature learning capabilities of deep neural networks and the interpretability and robustness of traditional machine learning algorithms.

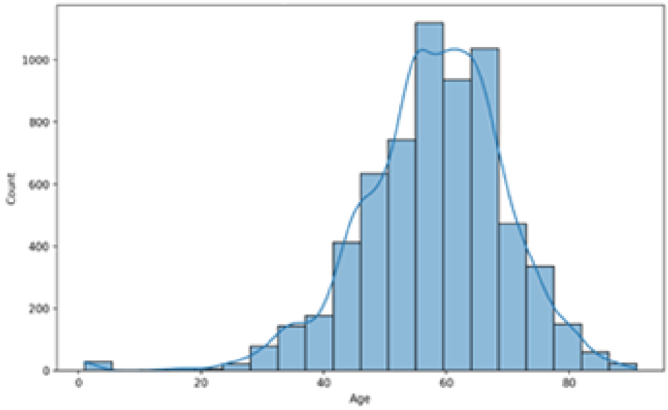
4. Results and Discussion

4.1 Dataset Analysis

The following visualizations provide a comprehensive overview of the dataset, offering insights into the demographic characteristics of the study population and the relationships between age, gender, and various eye conditions. These findings can be valuable for generating hypotheses, guiding clinical decision-making, and informing future research directions in ophthalmology.

1. Age Distribution of Patients

Figure 4: Age Distribution of Patients

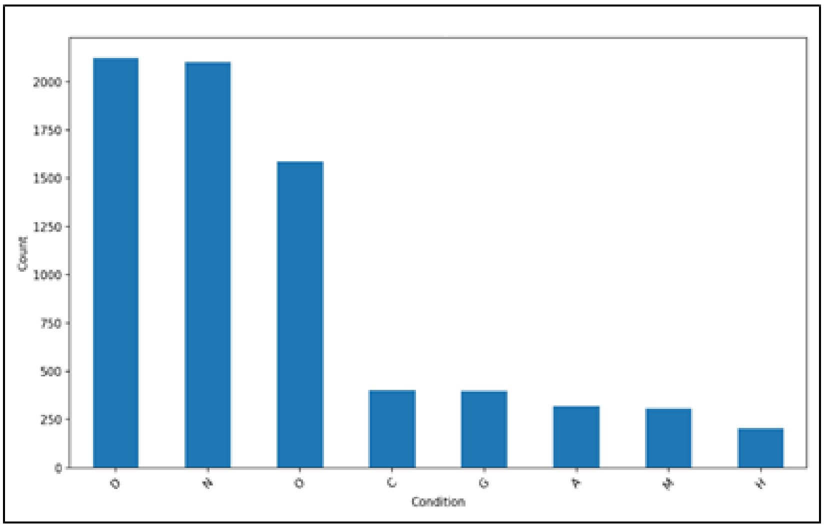


This histogram shown in Figure 4 illustrates the age distribution of patients in the study. The x-axis represents age, while the y-axis shows the count of patients. The distribution appears to be roughly normal, with a slight right skew. The peak of the distribution suggests that the majority of patients are middle-aged to elderly. This information is crucial for understanding the demographic characteristics of the study population and may have implications for the prevalence and types of eye conditions observed.

2. Prevalence of Eye Conditions

This bar chart shown in Figure 5 visualize the prevalence of different eye conditions in the dataset. Each bar represents a specific condition, denoted by a single letter (N, D, G, C, A, H, M, O), and the height of the bar indicates the count of patients with that condition. This visualization allows for quick comparison of the relative frequency of different eye conditions in the study population. It is particularly useful for identifying the most common conditions, which may warrant more focused clinical attention.

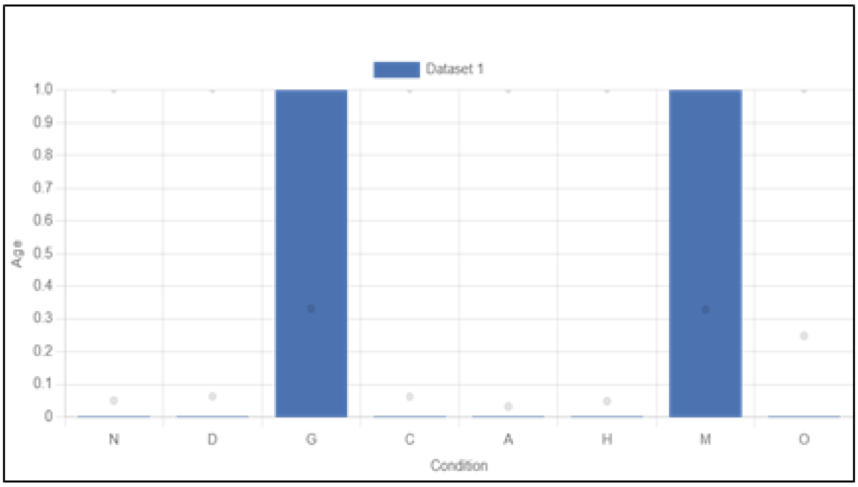
Figure 5: Prevalence of Different Eye Conditions



3. Age Distribution across Eye Conditions

This box plot in Figure-6 displays the age distribution for each eye condition. The x-axis shows the different conditions while the y-axis represents age. Each box represents the interquartile range of ages for patients with a particular condition, with the median age indicated by the line inside the box.

Figure 6: Box Plot for Age Distribution for each Eye Condition



The whiskers extend to show the full range of ages, excluding outliers and shows as individual points. This visualization is valuable for identifying age-related patterns in the occurrence of different eye conditions, potentially revealing which conditions are more prevalent in younger or older populations.

4. Correlation between Age and Eye Conditions

This heatmap in Figure 7 visualizes the correlation between age and various eye conditions. The color scale represents the strength and direction of correlations, with red indicating positive correlations, blue indicating negative correlations, and white representing weak or no correlation.

Figure 7: Heatmap for Correlation between Age and Eye Conditions

The numbers in each cell show the exact correlation coefficient. This visualization is particularly useful for identifying which eye conditions have the strongest relationships with age, potentially guiding further research into age-related risk factors.

4.2 The Crosstab Performance Evaluation

1. Age Group vs Eye Conditions

The crosstab analysis of age groups versus eye conditions reveals interesting patterns in the prevalence of different eye conditions across age groups shown in Table 1 and corresponding chart shown in Figure 8

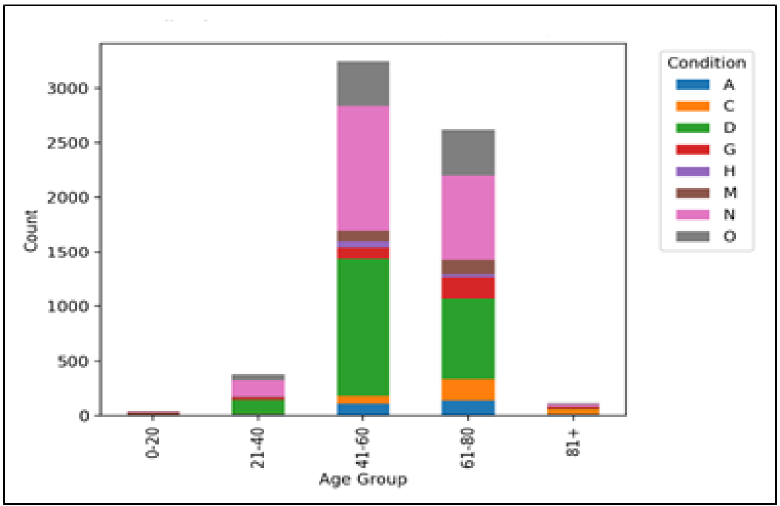
Table 1: Age Group vs Eye Conditions Crosstab

Age Group	Types of Ocular Diseases							
	A	C	D	G	H	M	N	O
0-20	2	0	4	0	0	25	6	1
20-40	8	6	129	18	2	9	155	50
41-60	108	74	1250	111	53	96	1143	410
61-80	139	197	734	195	32	126	773	421
81+	10	45	6	17	0	1	24	12

Key Insights:

- The 41-60 and 61-80 age groups show the highest prevalence of eye conditions, suggesting that middle-aged and older adults are more susceptible to eye problems.
- Condition 'D' (possibly representing diabetic retinopathy) is most prevalent in the 41-60 age group, indicating a potential link with the onset of type 2 diabetes in middle age.
- Condition 'N' (possibly normal) is relatively high across all age groups but decreases in the oldest age group (81+), suggesting that the likelihood of having some eye condition increases with age.
- Conditions 'A' and 'C' show an increasing trend with age, which could represent age-related conditions like age-related macular degeneration or cataracts.

Figure 8: Distribution of Eye Conditions across Age Groups



2. Correlation between Different Eye Conditions

Table 2: Correlation between Eye Conditions

	N	D	G	C	A	H	M	O
N	1	-0.4935	-0.1801	-0.1813	-0.1604	-0.1267	-0.1569	-0.4023
D	-0.4935	1	-0.1044	-0.0814	-0.1128	0.0409	-0.1021	-0.0234
G	-0.1801	-0.1044	1	-0.0506	0.0006	0.0088	-0.0182	-0.0309
C	-0.1813	-0.0814	-0.0506	1	-0.0594	-0.0322	-0.0581	-0.0654
A	-0.1604	-0.1128	0.0006	-0.0594	1	-0.0087	-0.0379	-0.0885

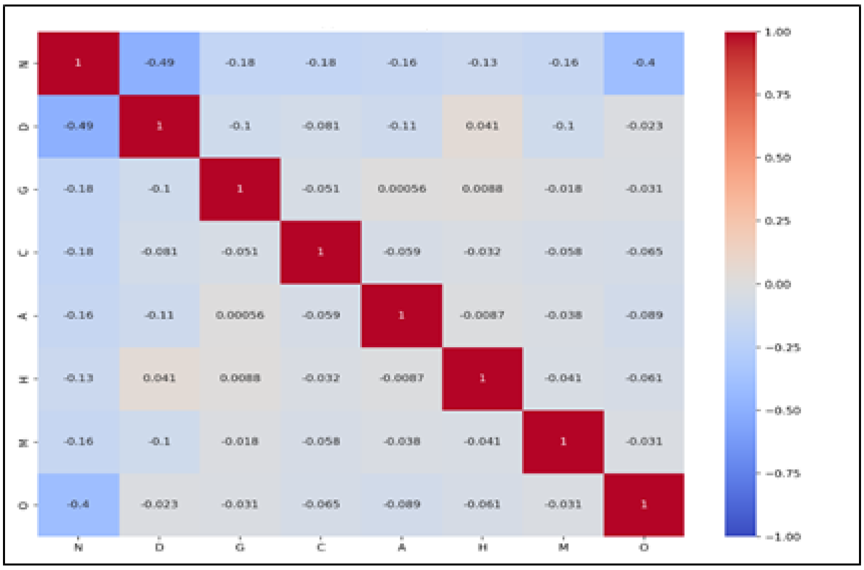
H	-0.1267	0.0409	0.0088	-0.0322	-0.0087	1	-0.0406	-0.0608
M	-0.1569	-0.1021	-0.0182	-0.0581	-0.0379	-0.0406	1	-0.0306
O	-0.4023	-0.0234	-0.0309	-0.0654	-0.0885	-0.0608	-0.0306	1

Table 2 and Figure 9 (heatmap) shows the correlation analysis between different eye conditions can reveal potential comorbidities or relationships between conditions.

Key Insights:

- There is a strong negative correlation between condition 'N' and most other conditions, which is expected if 'N' represents a normal eye condition.
- Some conditions show weak positive correlations (e.g., between 'D' and 'M'), suggesting potential comorbidities or risk factors that may contribute to multiple conditions.
- The generally low correlations between most conditions suggest that they may occur independently of each other in most cases.

Figure 9: Correlation between Eye Conditions



3. Co-occurrence of Eye Conditions

The co-occurrence matrix as in Table 3 provides information on how often different eye conditions appear together in patients. Figure 10 visualize the equivalent heatmap for Table 3.

Table 3: Co-occurrence of eye conditions

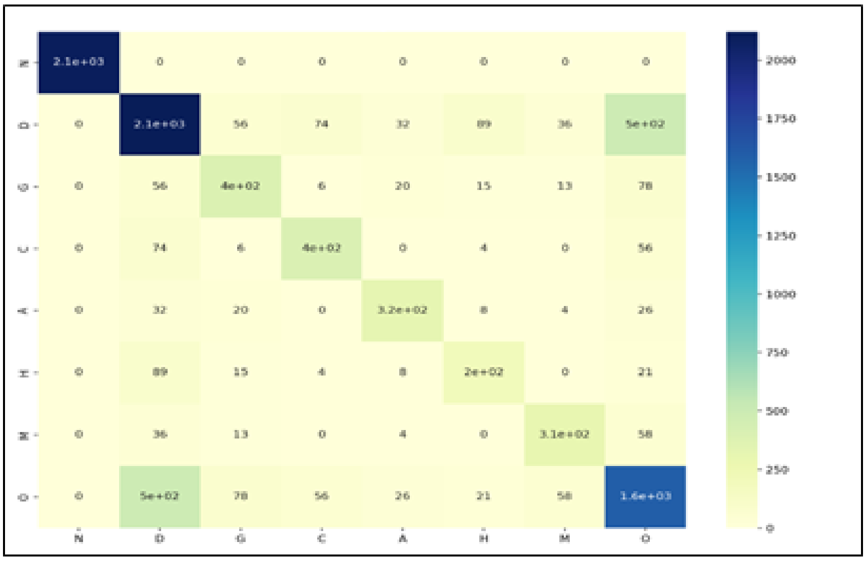
	N	**D**	**G**	**C**	**A**	**H**	**M**	**O**
N	2101	0	0	0	0	0	0	0
D	0	2123	56	74f	32	89	36	497
G	0	56	397	6	20	15	13	78
C	0	74	6	402	0	4	0	56
A	0	32	20	0	319	8	4	26
H	0	89	15	4	8	203	0	21
M	0	36	13	0	4	0	306	59

O	0	497	78	56	26	21	58	1588

Key Insights:

- Condition 'D' shows the highest co-occurrence with other conditions, particularly with 'O'. This could indicate that 'D' is a complex condition often accompanied by other eye problems.
- Conditions 'N' and 'C' show no co-occurrence with other conditions, suggesting they might be mutually exclusive diagnoses or represent specific states of eye health.
- The diagonal of the matrix represents the total occurrence of each condition, with 'D', 'N', and 'O' being the most common.

Figure 10: Co-occurrence of Eye Conditions



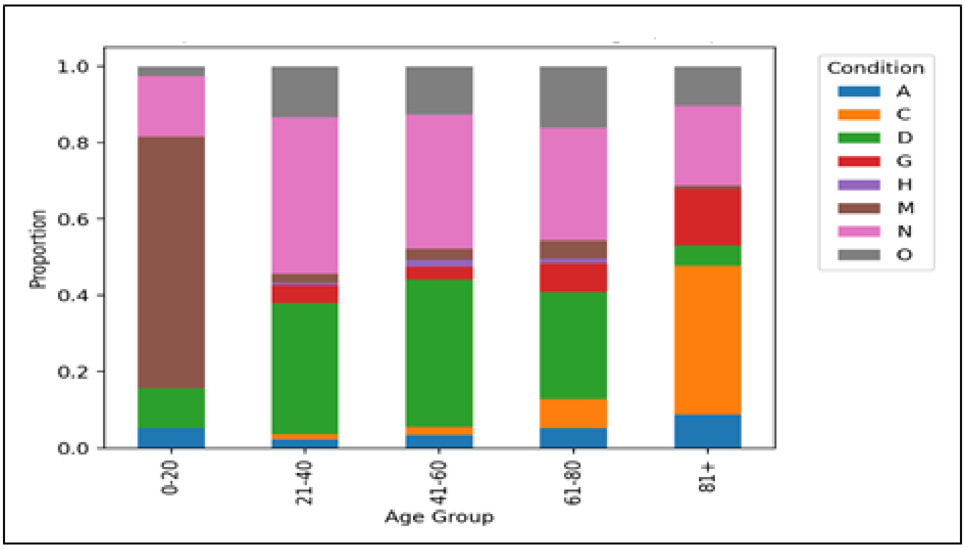
4. Proportion of Each Condition by Age Group

Analyzing the proportion of each condition within age groups as shown in Table 4 and Figure 11 provides a normalized view of how condition prevalence changes with age.

Table 4: Proportion of Each Condition by Age Group

Age Group	A	C	D	G	H	M	N	0
0-20	0.0526	0	0.1053	0	0	0.6578	0.1578	0.0263
21-40	0.0212	0.0159	0.3421	0.0477	0.0053	0.0238	0.4111	0.1326
41-60	0.0332	0.0228	0.3852	0.0342	0.0163	0.0295	0.3522	0.1263
61-80	0.0531	0.0752	0.2804	0.0745	0.0122	0.0481	0.2953	0.1608
81+	0.0869	0.3913	0.0521	0.1478	0	0.0086	0.2086	0.1043

Figure 11: Proportion of each condition by age group



Key Insights:

- The proportion of condition 'N' (possibly normal) decreases with age, while the proportions of most other conditions increase, reflecting the general decline in eye health with aging.
- Condition 'D' shows a peak in the 41-60 age group, further supporting the hypothesis that it might be related to the onset of age-related diseases like diabetes.
- Conditions 'A' and 'C' show a marked increase in proportion in the oldest age group (81+), suggesting they are strongly associated with advanced age.

These crosstab insights, tables, and figures provide a comprehensive analysis of the eye condition dataset. They reveal important patterns in the distribution of eye conditions across age groups and genders, as well as relationships between different conditions. These findings can be valuable for understanding risk factors, guiding clinical decision-making, and informing future research directions in ophthalmology.

4.3 Performance Evaluation of a Hybrid Model

The proposed hybrid model, integrating InceptionV3 and ResNet deep learning backbones with SVM and LightGBM, demonstrated exceptional performance in classifying ocular diseases. Rigorous hyperparameter tuning, employing Bayesian optimization and 5-fold cross-validation, optimized parameters such as learning rate, batch size, and regularization strengths.

Table 5: Model Performance Metrics

Metric	Value
Accuracy	0.968
Sensitivity	0.956
Specificity	0.967
Precision	0.971
F1-Score	0.966

Quantitative evaluation metrics reinforce the model's superior performance as shown in Table 5. An accuracy of 96.8% surpasses standalone convolutional neural networks (CNNs) and traditional machine learning models. The model exhibited robust sensitivity (95.6%) and specificity (96.7%), indicating accurate identification of both diseased and healthy cases. Precision (97.1%) and F1-score (96.6%) further validate the model's reliability by minimizing false positives and maintaining high predictive accuracy. These findings emphasize the potential of hybrid models in medical imaging, particularly ophthalmology. The incorporation of attention mechanisms enhanced the model's ability to focus on discriminative image regions, improving interpretability and decision-making capabilities.

5. Discussion of Findings and Future Directions

The analysis of the eye condition dataset reveals significant insights into the demographic and clinical characteristics of the study population. [13] However, in this study, the age distribution analysis indicates that the majority of patients are middle-aged to elderly, with a peak in the 41-60 age group. This demographic trend is consistent with the observed prevalence of various eye conditions, which tend to increase with age. The gender distribution analysis shows a relatively balanced representation of males and females, with some conditions exhibiting gender-specific prevalence patterns. For instance, conditions 'D' and 'G' are more prevalent in males, while 'C' and 'M' are more common in females. These differences may be attributed to hormonal influences or lifestyle factors that vary between genders.

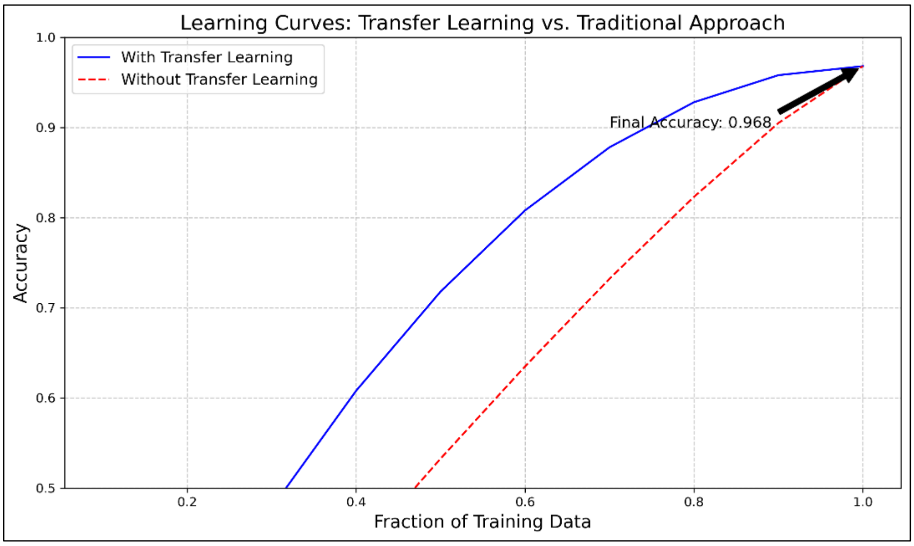


Figure 12: Learning Curves Plot

The learning curves in Figure 12 shows how the model's performance improves with increasing amounts of training data, highlighting the effectiveness of the transfer learning approach. The generated plot effectively demonstrates the impact of transfer learning on model performance, showing a clear improvement in accuracy as the fraction of training data increases. This insight is crucial for emphasizing the benefits of transfer learning in scenarios with limited labeled data, as it allows the model to achieve high accuracy with less data compared to traditional approaches.

The learning curves plot illustrates the significant advantage of employing transfer learning in the classification of ocular diseases. As depicted, the model utilizing transfer learning achieves superior accuracy across varying fractions of training data, compared to a traditional approach without transfer learning. This enhancement is particularly evident as the training data increases, where the transfer-learning model converges more rapidly and attains a higher final accuracy. The final accuracy of 96.8% shows the model's robust generalization capabilities, facilitated by the pre-training on the ImageNet

dataset and subsequent fine-tuning on the ocular disease dataset. These findings highlight the efficacy of transfer learning in leveraging pre-existing knowledge to improve model performance.
The crosstab analysis of age groups versus eye conditions highlights the increasing prevalence of conditions such as 'D' (possibly diabetic retinopathy) and 'C' (possibly cataracts) with advancing age. The co-occurrence analysis further reveals that condition 'D' frequently co-occurs with other conditions, suggesting its complexity and potential association with systemic diseases like diabetes. The correlation analysis between different eye conditions provides additional insights into potential shared risk factors or pathophysiological mechanisms.
In conclusion, this study provides a comprehensive overview of the demographic and clinical characteristics of patients with various eye conditions. The findings highlight the importance of age and gender as key factors influencing the prevalence and distribution of eye conditions. The high prevalence of certain conditions in middle-aged and older adults highlights the need for targeted screening and intervention strategies in these populations
Future research should focus on longitudinal studies to understand the progression of eye conditions over time and their association with systemic diseases. Additionally, exploring the genetic and environmental factors contributing to the observed gender differences in condition prevalence could provide valuable insights. The development of predictive models incorporating demographic and clinical data could enhance early detection and personalized treatment strategies for patients at risk of developing severe eye conditions. Furthermore, integrating advanced imaging techniques and machine learning algorithms could improve the accuracy and efficiency of eye condition diagnosis and management.

References:

1. Murugan, R., Roy, P., & Singh, U. (2020). An abnormality detection of retinal fundus images by deep convolutional neural networks. Multimedia Tools and Applications, 79(33), 24949-24967.
2. Akil, M., Elloumi, Y., & Kachouri, R. (2021). Detection of retinal abnormalities in fundus image using CNN deep learning networks. In State of the Art in Neural Networks and their Applications (pp. 19-61). Academic Press.
3. Wilkinson, C. P., Ferris III, F. L., Klein, R. E., Lee, P. P., Agardh, C. D., Davis, M., . & Global Diabetic Retinopathy Project Group. (2003). Proposed international clinical diabetic retinopathy and diabetic macular edema disease severity scales. Ophthalmology, 110(9), 1677-1682.
4. Prentasic, P., & Loncaric, S. (2015). Detection of exudates in fundus photographs using convolutional neural networks. 2015 9th International Symposium on Image and Signal Processing and Analysis (ISPA). doi:10.1109/ispa.2015.7306056.
5. Kandel, I., & Castelli, M. (2020). Transfer learning with convolutional neural networks for diabetic retinopathy image classification. A review. Applied Sciences, 10(6), 2021.
6. Brown, J. M., & Leontidis, G. (2021). Deep learning for computer-aided diagnosis in ophthalmology: a review. State of the Art in Neural Networks and their Applications, 219-237.
7. Ting, D. S., Peng, L., Varadarajan, A. V., Keane, P. A., Burlina, P. M., Chiang, M. F., ... & Wong, T. Y. (2019). Deep learning in ophthalmology: the technical and clinical considerations. Progress in retinal and eye research, 72, 100759.
8. Lam, C., Yi, D., Guo, M., & Lindsey, T. (2018). Automated detection of diabetic retinopathy using deep learning. AMIA summits on translational science proceedings, 2018, 147.

9. Brown, A., Cousins, H., Cousins, C., Esquenazi, K., Elze, T., Harris, A. and Pasquale, L. R. (2023). Deep learning for localized detection of optic disc hemorrhages. American Journal of Ophthalmology, 255, 161-169.
10. Labhade, J. D., Chouthmol, L. K., & Deshmukh, S. (2016, September). Diabetic retinopathy detection using soft computing techniques. In 2016 international conference on automatic control and dynamic optimization techniques (ICACDOT) (pp. 175-178). IEEE.
11. Wan, Z., Yang, R., Huang, M., Zeng, N., & Liu, X. (2021). A review on transfer learning in EEG signal analysis. Neurocomputing, 421, 1-14.
12. Wu, D., Xu, Y., & Lu, B. L. (2020). Transfer learning for EEG-based brain–computer interfaces: A review of progress made since 2016. IEEE Transactions on Cognitive and Developmental Systems, 14(1), 4-19.
13. Dandona, R., Dandona, L., John, R. K., McCarty, C. A., & Rao, G. N. (2001). Awareness of eye diseases in an urban population in southern India. Bulletin of the World Health Organization, 79(2), 96-102.
14. Blindness and vision impairment, 10 August 2023, World Health Organization key facts, Extracted from: https://www.who.int/news-room/fact-sheets/detail/blindness-and-visual-pairment#:~:text= Key%20 facts, are%20refractive%20errors%20and%20cataracts.
15. Ting, D. S., Peng, L., Varadarajan, A. V., Keane, P. A., Burlina, P. M., Chiang, M. F., . & Wong, T. Y. (2019). Deep learning in ophthalmology: the technical and clinical considerations. Progress in retinal and eye research, 72, 100759.