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A Conceptual Artificial Intelligence-Driven Framework for Detection of Eye Diseases in Nigeria

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ABSTRACT

Unavailability of accurate and timely diagnosis did not allow efforts made by health professionals to yield any meaningful result in Nigeria. Nigeria is the most populous country in Africa and home to over 200 million people, making it one of the most densely populated countries in the world. It is estimated that 4.25 million adults aged ≥ 40 years have moderate to severe eye disease or blindness. Allergic conjunctivitis (17.8%), age-related macular degeneration, cataracts, glaucoma (16.7%), cornea opacity, refractive errors (14.3%), and ocular trauma (21.7%) are known to be the major causes of eye disorders in Nigeria. Ocular injury was more common in males ($p=0.002$) and children aged 6–10 years, and 87.1% of these cases were closed-globe injuries, 80% of blindness cases are preventable and curable. Thus, artificial intelligence (AI) techniques, especially deep learning (DL) have emerged as important technique in handling very complex tasks. However, AI and DL are yet to be maximized in ocular medicine. This paper explored the concepts of deep learning methods in eye disease detection and classification. The exploration proposed a single modality and multimodal models, the models would be trained on a large multiclass dataset comprising of age, symptoms, laboratory test results, x-ray image results, diseases diagnosed and medical imaging (OCT, Fundus image, etc.) respectively. These would be obtained from the medical records of previously diagnosed and treated eye diseases. The techniques will improve accurate and timely diagnosis of eye diseases.

INTRODUCTION

The eye is an essential part of the human body, it is an organ that is responsible for vision, vision is the most dominant of our senses, which plays a vital role in all aspects and phases of our lives. We take vision for granted, but without vision, there is difficulty in learning, walking, reading, participating in school, and to work. Youngs and Adults with vision impairment can experience delayed motor, language, emotional, social & cognitive development, with lifelong consequences and lower rates of employment, higher rates of depression, anxiety, social isolation, difficulty walking, a higher risk of falls and fractures, a greater likelihood of early entry into nursing or care homes respectively (Hamid *et al.*, 2024; WHO, 2026). Atleast 2.2 billion people worldwide have vision impairment (WHO, 2019; WHO, 2026). Refractive errors, Cataract and age-related eye diseases are the most common causes of vision impairment (WHO, 2026). The World Health Organization (WHO) estimates that between 2020 and 2030, the global number of people with glaucoma will increase by 1.3 times (from 76 million to 95.4 million) and the global number of people with age-related macular degeneration (AMD) will increase by 1.2 times (from 195.6 million to 243.3 million). Also, as a result of an aging population, a rise in the number of people with cataracts (especially those aged 70 years and over) has been projected. Moreover, changes in lifestyle and exposure to environmental factors (air pollution, low humidity, and winds) may also increase the number of people with eye irritation or dry eye symptoms.

Eye diseases are conditions that affect any part of the eye, and include conditions that affect the structures immediately around the eyes. These conditions can be acute (they develop quickly) or chronic (they develop more slowly and last a long time) (Cleveland Clinic, 2024). These diseases present serious and complex issues in ophthalmology. They encompass a wide range of health conditions, Li *et al.* (2023) classifies ophthalmic diseases to two segments; posterior-segment and anterior-segment, identifying posterior-segment eye diseases as Glaucoma, diabetic retinopathy (DR), age-related macular degeneration (AMD), and also anterior-segments eye diseases as cataract, keratitis, keratoconus.

The main causes of eye diseases are in four categories; age, genetic, lifestyle and environmental factors, age is the most important factor for numerous eye diseases, and genetic predisposition also is a well-described risk factor for age-related eye diseases, there are also risk factors related to lifestyle behaviors; tobacco use, nutrition, and occupational exposure are common lifestyle factors associated with eye disorders and diseases (Kamińska *et al.*, 2023). Smokers are at higher risk of AMD, cataracts, and optic neuropathies. Diabetic retinopathy is a serious complication of Diabetes Mellitus that can be prevented

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or delayed with lifestyle changes and proper control of blood glucose levels (Safaa, 2023; Shimu *et al.*, 2025). Awareness of risk factors for eye diseases is necessary to implement eye disease prevention at the individual and population levels. Environmental causes of eye diseases include underlying health issues, drug and alcohol abuse, infections and injury.

The major causes of blindness in young and adults with eye diseases have been found to be late detection of diseases and misdiagnosis due to confusions in diagnosing diseases with similar symptoms and data quality (WHO, 2019; SEIEH, 2023; WHO, 2026). Timely and accurate diagnosis if met with appropriate treatment promises a better result. Some of the common means of diagnosing eye diseases are eye exam, slit-lamp examination, fundoscopy, refraction test and visual field test.

Evolution of Artificial Intelligence in ophthalmology as illustrated in figure 1 currently leverages Deep Learning approach to classify data from high-resolution ophthalmic imaging. Its application is very promising, Numerous studies has shown cases of eye disease detection on ophthalmic images with the aid of deep learning frameworks. ocular diseases often rely heavily on image recognition, based on this technique, diabetic retinopathy (DR), glaucoma, and age-related macular degeneration (AMD) can be accurately detected from fundus images, and keratitis, pterygium, and cataract can be precisely identified from slit-lamp images and also observing macular and choroidal abnormalities, bleeding, vessel defects, and glaucoma can be detected efficiently with retinal scans (Han, 2022; Li *et al.*, 2023).

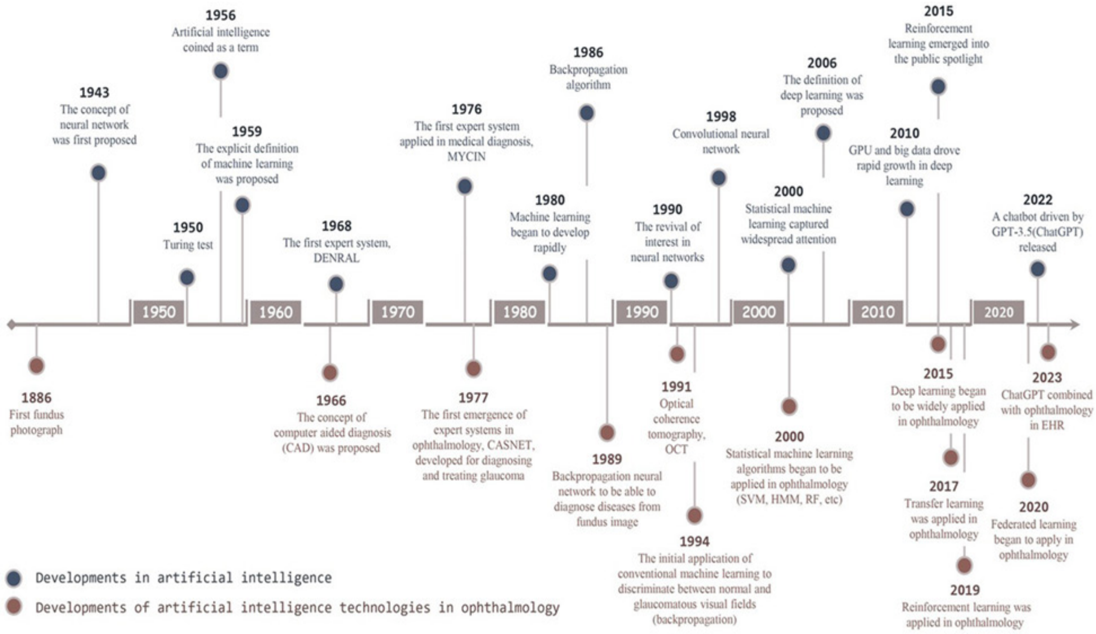

Figure 1: Timeline of the progress of AI technologies in ophthalmology (bottom circles), compared with the development of AI (top circles).
Source: (Yin et al., 2025).

LITERATURE REVIEW

Extensive literature indicates that deep learning (DL) applications in eye disease have primarily relied on single-modality paradigms, principally computer vision analyzing high-resolution retinal imaging. While these frameworks achieve high diagnostic accuracy for isolated conditions, clinical eye care in resource-limited environments like Nigeria requires a more holistic diagnostic framework. The Traditional Machine Learning methods that have been used so far includes CNN, SVM, transfer learning, ensemble learning, deep learning, random forest, KNN, and feature engineering, these methods has been applied to various image datasets such as retina images, fundus images and OCT images, key findings and results of these studies are significant and demonstrate the potential of machine learning methods in improving the accuracy, sensitivity, and specificity of retinal disease detection and classification, achieving high accuracy in diabetic retinopathy detection, improving glaucoma diagnosis with an AUC of 0.92, reducing false positives in AMD detection, achieving high accuracy in distinguishing various retinal diseases, identifying important features for grading diabetic retinopathy, generating synthetic images for improved model training, enhancing diagnostic accuracy, and improving the sensitivity and specificity in detecting retinopathy (Raut *et al.*, 2024).

Harti *et al.* (2025) compared various AI-based diagnostics models with clinical tests employed by ophthalmologist, targeting studies between 2020 and 2025 including 30 original peer-reviewed articles identifying deep learning models including; U-shaped convolutional networks (U-Net), Densely connected convolutional networks (DenseNet), Residual networks (ResNet), Generative adversarial Networks (GAN), and transformers, as a diagnostics tools giving promising accuracy and performance ranging from 82% to 99% , where few studies performed external validation or addressed inter expert variability. The findings confirm AI's potential in dry eye diseases diagnosis but emphasize gaps in data diversity, clinical use, and reproducibility.

Okokpujie *et al.* (2025) offered a web-based application for real-time approach to classify eye disease from fundus image, improving user access. Three pre-trained CNN model were used namely; ResNet-50, Inception-V3, and MobileNetV3. The models were trained on dataset of 8,000 fundus images, subdivided into four classes; cataract, glaucoma, diabetic retinopathy, and normal eyes. The performance was evaluated in 3-ways (normal eye and two diseases), and 4-ways (normal eye and three diseases). ResNet-50 has higher performance with 98% and 97% accuracy in the respective classification compared to inceptionV3 and MobileNet, likewise (Priyadharshini *et al.*, 2026). This research findings reveals potentials of CNNs in the healthcare industry and increasing access to quality diagnostic technologies while using fundus imaging only.

Kim *et al.* (2022) propose an automatic method using deep learning algorithms to segment the optic disc and cup and to estimate the key measures. The proposed method comprises three steps: The Region of Interest (ROI) (location of the optic disc) detection from a fundus image using Mask R-CNN, the optic disc and cup segmentation from the ROI using the proposed Multiscale Average Pooling Net (MAPNet), and the estimation of the key measures. The segmentation results using 1099 fundus images show 0.9381 Jaccard Index (JI) and 0.9679 Dice Coefficient (DC) for the optic disc and 0.8222 JI and 0.8996 DC for the cup. The average CD, CD area, and RD ratio errors are 0.0451, 0.0376, and 0.0376, respectively. The average disc, cup, and rim radius ratio errors are 0.0500, 0.2257, and 0.2166, respectively. The method performs well in estimating the key measures and shows potential to work within clinical pathways once fully implemented. The research did not specifically focus on one eye diseases and was design for the classification of glaucoma only.

Alyoubi *et al.* (2020) reviewed the most recent automated systems of diabetic retinopathy detection and classification that used deep learning techniques. The common fundus DR datasets that are publicly available was described with deep-learning techniques been used. He discussed that most researchers use the CNN for the classification and the detection of the DR images due to its efficiency. Although the review is only on diabetic retinopathy (DR), and as well the useful techniques that can be utilized to detect and classify DR using deep learning was discussed.

An automatic detection method of age-related macular degeneration (AMD) from optical coherence tomography (OCT) images based on deep learning and a local outlier factor (LOF) algorithm was the focus of He *et al.* (2022). A ResNet-50 model with L2-constrained softmax loss was retrained to extract features from OCT images and the LOF algorithm was used as the classifier. The proposed method was trained on the UCSD dataset and tested on both the UCSD dataset and Duke dataset, with an accuracy of 99.87% and 97.56%, respectively. Even though the model was only trained on the UCSD dataset, it obtained good detection accuracy when tested on another dataset. Comparison with other methods also indicates the efficiency of the proposed method in detecting AMD. Likewise, the research did not specifically focus on common eye diseases and was successfully design for the classification of age-related macular degeneration using oct scan image only.

Apart from the traditional machine learning methods of detecting cataract which is prone to misclassification However, deep learning's convolutional neural network (CNN) can be used for pattern recognition which can help automate image classification, Weni *et al.* (2021) conducted research to increase the accuracy value and minimize data loss in the process of cataract identification by performing an experience namely the manipulation process was carried out by changing epochs. The results of this study indicate that the addition of epochs affects accuracy and loss data from CNN. By comparing variety of epoch values, it can be ignored that the higher the age values used, the higher the value of the model. In this study, using the epoch 50 value reached the highest value with a value of 95%. Based on the model that has been made it has also been successful to receive images according to the specified class. After testing accurately, 10 images achieved an average accuracy of 88%. The model was found to be far accurate than the conventional methods but the study centered on cataract only.

Alquran *et al.* (2022) in their research highlighted the bottleneck on using clinical method that use slit-lamp images can be tiresome, expensive, and time-consuming and instead, a deep learning approach was proposed to diagnose corneal ulcers, enabling better, improved treatment. using automatic deep learning (RestNet101) feature extraction resulting in ~93% accuracy using the 30 most significant features extracted using various dimensionality reduction techniques. On the other hand, automatic deep learning feature extraction discriminated severity grading with a higher accuracy than type grading regardless of the number of features used. Identifying corneal ulcers at an early stage is a preventive measure that reduces aggravation and helps track the efficacy of adapted medical treatment, improving the general public health in remote, underserved areas.

Bansal *et al.* (2025) reviewed transformative application of artificial intelligence in ophthalmology with a simple CNN model for the detection of eye diseases. The model was presented to detect eye disease after being trained and tested using eye diseases datasets comprising of images of the retina, with preprocessing by applying techniques of data augmentation; resizing, flipping, and rotation. Results demonstrate the potential of artificial intelligence, more importantly CNN models to enhance the accuracy and speed of eye diseases diagnosis, reducing the workload of ophthalmologist and improving patients' outcomes. It also discussed challenges and limitation of artificial intelligence in ophthalmology, such as; the need for large and diverse dataset, the importance of interpretability and explainability, and the possible ethical and regulatory issues.

Casado-Moreno *et al.* (2025) evaluates the effectiveness of deep learning techniques applied to raw Scheimpflug corneal images for keratoconus detection, with a particular focus on forme fruste (FF) keratoconus, which refers to preclinical cases. Using an original dataset of 22,750 images from 910 eyes, a deep learning model based on transfer learning with a pre-trained VGG16 architecture was trained, incorporating specific preprocessing steps and data augmentation strategies. The approach achieved an overall accuracy of 90.70%, with a sensitivity of 80.57%, and a specificity of 80.56% for FF keratoconus classification, and an AUC of 0.89. For clinical keratoconus, the model demonstrated a sensitivity of 93.28%, a specificity of 99.40%, and an AUC of 1.00. These findings highlight the potential of leveraging raw Scheimpflug images in deep learning-based keratoconus detection only.

Kavianfar *et al.* (2021) also reviewed 37 case studies; one dealt with exophthalmos, three strabismus, two with eye lid tumor, three with keratoconus, seven with cataracts, one with myopia, glaucoma, diabetic retinopathy, each one of nine studies, and noted that deep learning algorithms are highly accurate, sensitive and specific for diabetic retinopathy, age-related macular degeneration, and glaucoma, which are the most prevalent visual disorder. The study concluded the use of artificial intelligence should be seen as extra tools to supports physician rather than as a substitute for them; As a result, the application faces a variety of challenges including the validation of algorithm, patient acceptance of these technologies, as well as the education and training of healthcare professionals.

MATERIALS AND METHODS

This study employed a narrative review to demonstrate the capabilities of deep learning techniques for detecting and classifying eye disease. A reputable database of publications related to Artificial Intelligence in Ophthalmology was explored to identify relevant articles covering publications between 2020 and 2026. These helps to identify advances of artificial intelligence in ophthalmology. The keyword used in the search are; artificial intelligence in healthcare, artificial intelligence in ophthalmology and artificial intelligence in eye disease. The processes are as illustrated in figure 2. Initial discovery entails searching google scholar, ResearchGate and Scopus for AI, machine learning, and deep learning eye disease related journals or articles and selecting 20 to 30 highly-cited foundational and recent papers. Screening entails scanning introductions to identify major eye diseases addressed and methods used. Review entails noting which techniques consistently score highest identify recurring limitations and gaps. Synthesis entails comparing different authors' perspectives on model accuracy and connecting how their preprocessing impacts final classification success while arriving at a conclusion verdict on the best approach.

Figure 2: Method.

RESULTS AND DISCUSSION

Most machine learning and deep learning models developed so far for predicting or detecting eye diseases are disease specific, they are mostly developed for one eye disease, one data class of eye diseases occurrence using Traditional CNN, SVM, transfer learning, ensemble learning, deep learning, random forest, KNN, feature engineering, ANN-CNN or CNN-CNN architecture and lack of real-world clinical testing. Although some of these methods perform satisfactorily, major anterior and posterior eye diseases are very delicate because of their asymptomatic nature in their early stages, testing different models to be able to identify the particular disease will waste so much time. It will also make disease diagnosis very expensive and cumbersome which may result in blindness of several patients. This paper therefore aims to give a simple and dual modality approach (image data and clinical or textual data) of deep learning model that would be able to classify different eye diseases especially those peculiar to Nigeria.

Proposed Deep Learning Framework for Eye Diseases Detection and Classification

The proposed and best model development and architecture for timely detection of eye disease including those in their early / asymptomatic state will be the use of clinical records, anonymizing the patient's personal identifiable information (i.e., Name) For ethical consideration (FGN, 2023; eHealth4Heveryone, 2023; Jayan, 2024), and the scan images making the usage of textual and image data modality appropriate. They are discussed below and represented in the figure 3 and 4;

1. Textual data approach: Since the dataset contains clinical information (age, symptoms, lab results, and diagnoses etc.), textual data preprocessing (i.e., data Integration & Cleaning, tokenization, noise removal, stemming & lemmatization and vectorization) will be done, this will employ natural language processing (NLP) techniques and advance machine learning (deep learning) algorithm like RNN (LSTM) and ANN for the model implementation and

development and will be evaluated on its accuracy, precision, recall and f1score.

2. Image data approach: This is most common approach so far using image data set with preprocessing like; resizing & aspect ratio, enhancement (CLAHE; Contrast Limited Adaptive Histogram Equalization), normalization and denoising, employing machine learning (deep learning) algorithm like CNN-LSTM and commonly CNN-CNN architecture (e.g., ResNet50, InceptionV3 and MobileNetV3, etc.), evaluated on its accuracy, precision, recall and f1score.
3. Textual & Image data approach: This approach will give a faster and more easy detection and classification as the dataset type is not a barrier, with preprocessing combination of i & ii above employing machine learning (deep learning) algorithm ANN-LSTM-CNN architecture, evaluated on its accuracy, precision, recall and f1score.

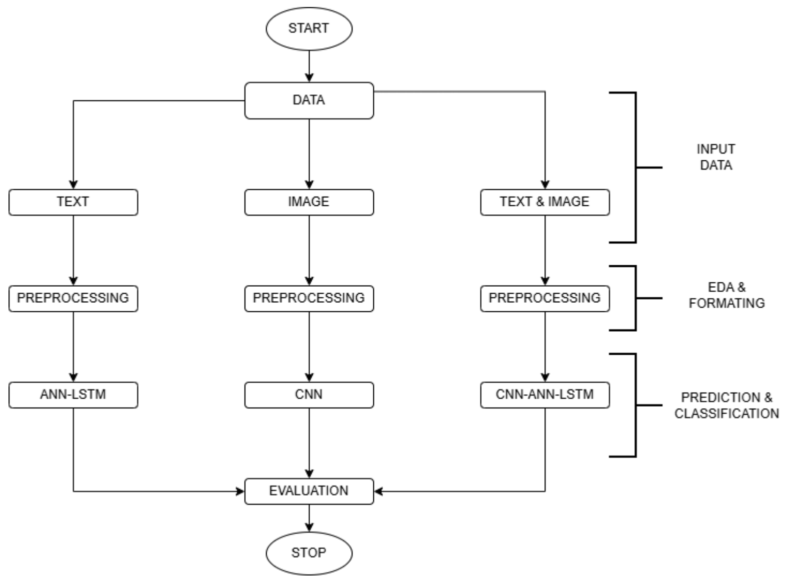

Figure 3: Flow chart of system implementation.

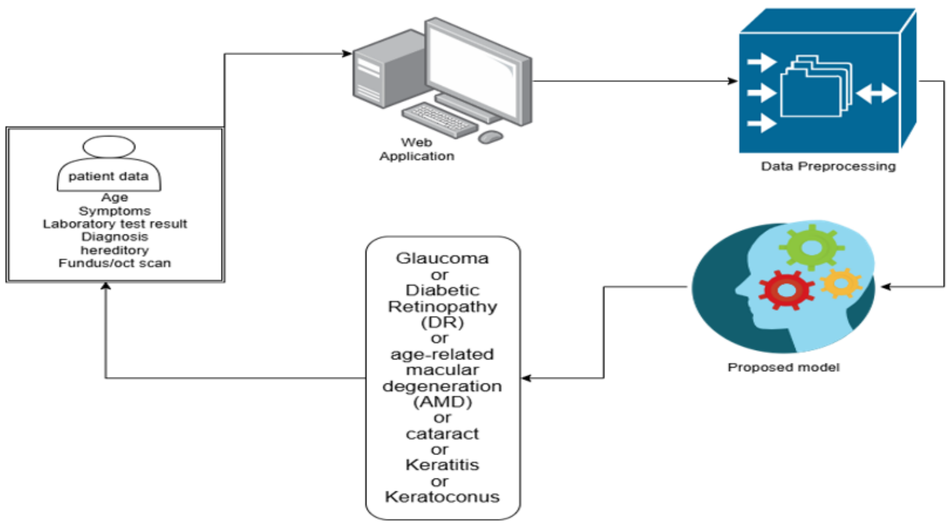

Figure 4: Architecture of system implementation.

Implementation

ANN (Artificial Neural Network)

Artificial Neural Network (ANN) as expressed in equations 1 and 2 recieves initial linear inputs transformed by their weights (W) and bias (b) and then passed through the activation function to capture complex patterns in the clinical datasets.

Modelling operation;

$$z^{(l)} = W^{(1)}a^{(l-1)} + b^{(l)} \quad (1)$$

$$a^{(l)} = f(z^{(l)}) \quad (2)$$

Where (W) is the weights, (b) is bias, (a) is the activation vector from the previous layer, and (f) is a non-linear function (e.g., ReLU, Sigmoid) (Odeyemi *et al.*, 2024)

CNN (Convolutional Neural Network)

Convolutional Neural Network (CNN) as expressed in equations 3 and 4 slides a kernel filter (K) over and image (I) using a 2D cross-correlation (*) to extract spatial feature maps for eye disease recognition on ophthalmic imagings.

Modelling operation;

$$(I * K)(i, j) = \sum m \sum n\, I(i - m, j - n) K(m, n) \qquad (3)$$

$$A_l = f(I * K + b) \qquad (4)$$

Where A_l is the feature map, and * denotes the 2D cross-correlation operation (Odeyemi *et al.*, 2024).

LSTM (Long Short-Term Memory)

Long Short-Term Memory (LSTM) as expressed in equations 5 to 10 and and shown figure 5 manages temporal clinical data using three gating mechanisms; the forget gate (f_t) discards irrelevant past data, while the input gate (i_t) updates new information, and the output gate (o_t) regulates the hidden state (h_t). The Hadamard product (Θ) ensures precise, and element-wise cell state updates (c_t) to track patient data variations over time without information loss.

Modelling operation;

Forget Gate: $\boldsymbol{f_t} = \sigma(w_f.[h_{t-1}, x_t] + b_f$ (5)

Input Gate: $\boldsymbol{i_t} = \sigma(w_i.[h_{t-1}, x_t] + b_i$ (6)

Candidate Cell State: $\tilde{\boldsymbol{c}}_t = \tanh(w_c.[h_{t-1}, x_t] + b_c$ (7)

Cell State Update: $\boldsymbol{c_t} = f_t \odot c_{t-1} + i_t \odot \tilde{\boldsymbol{c}}_t$ (8)

Output Gate: $\boldsymbol{o_t} = \sigma(w_o.[h_{t-1}, x_t] + b_o$ (9)

Hidden State: $\boldsymbol{h_t} = o_t \odot tanh(c_t)$ (10)

Where σ is the sigmoid function, Θ is the Hadamard/element-wise product, and h is the hidden state.(Odeyemi *et al.*, 2024).

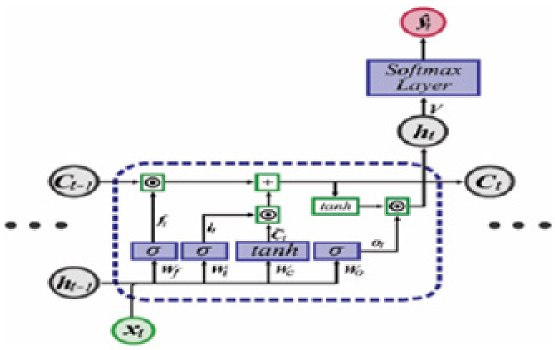

Figure 5: Architecture of LSTM model,
Source: (Gill et al., 2022)

Hybrid CNN + LSTM modelling (Spatial-Temporal): Extracts high-level spatial features from inputs (like images or multivariate) using CNN, and processes the extracted sequence features over time using LSTM.

i. Feature Extraction: $F_t = CNN(x_t)$ (11)
ii. Sequence Modeling: $h_t, c_t = LSTM(F_t, h_{t-1}, c_{t-1})$ (12)

Hybrid CNN + ANN modelling (Spatial-Classification) Extracts spatial hierarchies using CNN, flattens them, and processes the global features through traditional dense layers as described in Eqs. 13-15 and shown in figure 6.

i. Convolution: $F = CNN(x_t)$ (13)
ii. Flatten: $F_{flat} = Flatten(F)$ (14)
iii. Final Output: $Y = ANN(W.F_{flat} + b)$ (15)

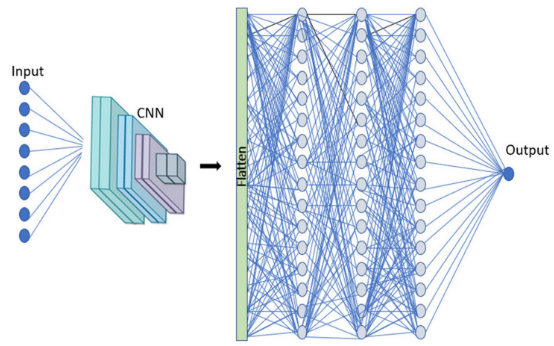

Figure 6: Architecture of Hybrid CNN + ANN model
Source: (Bamisile et al., 2022)

Hybrid LSTM + ANN modelling (Sequential-Classification) Processes a series over time using LSTM and feeds the final hidden state to dense layers to output the prediction as described in Eqs. 16 - 17 and shown in figure 7.

i. Sequential processing: $h_t = LSTM(x_t, h_{t-1}, \ldots, x_1)$ (16)
ii. Output mapping: $Y = ANN(W.h_t + b)$ (17)

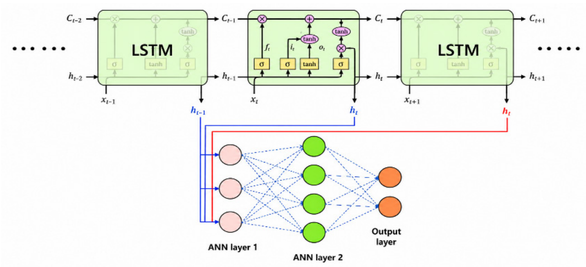

Figure 7: Architecture of Hybrid LSTM + ANN model
Source: (Odeyemi et al., 2024).

Hybrid CNN + LSTM + ANN Modelling

This architecture extracts spatial features, learns temporal dependencies from those features, and maps them to final output probabilities via dense layers. It follows a stacked sequential pipeline as described in Eqs. 18 – 20 and shown in figure 8.

- CNN Phase (Spatial Feature Extraction): Extracts local structural or spatial features for each time step or frame:

$$F_{x,y,c,t} = Conv2D(x_{x,y,c,t}) \qquad (18)$$

- LSTM Phase (Temporal Sequence Learning): Takes the flattened CNN features per step and tracks temporal changes in feature states:

$$h_t, c_t = LSTM(Flatten(F_t), h_{t-1}, \boldsymbol{c_{t-1}}) \qquad (19)$$

- ANN Phase (Output Mapping): Passes the final recurrent hidden state ht through the dense layers to generate the network prediction:

$$\hat{Y} = \frac{Softmax}{\sigma(W.h_t + b)} \qquad (20)$$

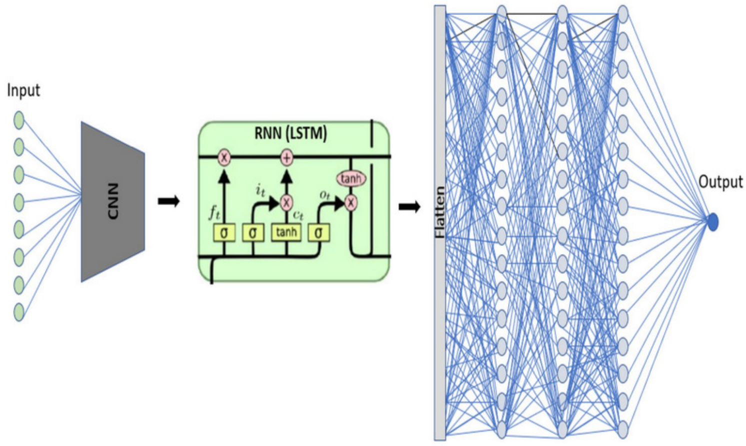

Figure 8: Architecture of Hybrid CNN + LSTM + ANN model
Source: (Bamisile et al., 2022)

Performance Evaluation Metrics

This research being a classification task would be evaluated using the best set of evaluation metrics for deep learning algorithms; accuracy, precision, recall, F1 score and AUC-ROC. These would be employed as the evaluation metrics, as they take into consideration the true positive, true negative, false positive and false negative values during evaluation. These metrics would serve as a good performance metrics for this study due to its proven application and results.

- Accuracy: This metric calculates overall prediction correctness as a ratio of the sum of correctly predicted positive (True Positive TP) and correctly predicted negative (True Negative TN) to the total number of events (Eq. 21) (Odeyemi *et al.*, 2024). This is expressed mathematically thus:

$$Accuracy = \frac{TN+TP}{TN+FN+TP+FP} \quad (21)$$

Where:
TP – True Positive
TN – True Negative
FP – False Positive
FN – False Negative

- Precision: This metric computes the quality of positive predictions by calculating their correctness. This is expressed in Eq. 22 as the ratio of correct positive prediction (True Positive TP) to that of the sum of correct positive prediction (True Positive TP) and wrong positive prediction (False Positive FP) (Odeyemi *et al.*, 2024).

$$Precision = \frac{TP}{TP+FP} \quad (22)$$

- Recall: Recall or sensitivity measures how the model is able to detect the positive events correctly. As shown in Eq. 23, it is expressed as the percentage of accurately predicted positive events out of all the positive events (Odeyemi *et al.*, 2024). It is expressed mathematically thus:

$$Recall = \frac{TP}{TP+FN} \quad (23)$$

- F1score: This metric is expressed as the harmonic mean of the precision and recall of the classification model. As shown in Eq. 24, precision and recall contribute equally to the score to make F1 score correctly express the reliability of the model (Odeyemi *et al.*, 2024).

$$F1\ score = 2 \times \frac{\text{precision} \times \text{Recall}}{\text{precision}+\text{Recall}} \quad (24)$$

- AUC-ROC: Area under the curve-receiver operator curve (AUC-ROC) is another evaluation metric. ROC is a probability curve, and AUC represents the degree or measure of separability. AUC-ROC uses sensitivity (true positive rate) and specificity (false positive rate) (Raut *et al.*, 2024).

CONCLUSION

Eye disease is one of the major challenges in public health, especially in developing nations due to diagnostic delays and clinical assessment errors. Current methods used in the diagnosis of eye diseases are essential but faced limitations because of single data modality i.e., fundus, oct, retina images which introduces significant diagnostic vulnerabilities, particularly in resource-constrained and underserved regions where access to specialized multimodal imaging infrastructure remains highly fragmented or entirely unavailable.

Artificial intelligence in health systems especially in eye care proved promising in the detection of eye diseases. To solve the limitations, this paper demonstrates various deep learning conceptual frameworks that would help improve the accuracy and timely diagnosis of eye diseases solving the problem of data modality, diversity and inclusivity. However, it is important to note that while deep learning provides accurate diagnostics, it does not replace the expertise of medical professionals in clinical diagnosis, rather it helps mitigate diagnostic errors induced by clinician fatigue during extended operational hours and bridge critical care gaps in regions afflicted by severe specialist shortages. Future research will focus on the implementation of the concepts established.

REFERENCES

Alquran, H., Al-Issa, Y., Alsalatie, M., Mustafa, W. A., Qasmieh, I. A., & Zyout, A. (2022). Intelligent diagnosis and classification of keratitis. *Diagnostics, 12*(6), 1344. https://doi.org/10.3390/diagnostics12061344

Alyoubi, W. L., Shalash, W. M., & Abulkhair, M. F. (2020). Diabetic retinopathy detection through deep learning techniques: A review. *Informatics in Medicine Unlocked, 20,* 100377.https://doi.org/10.1016/j.imu.2020.100377

Bamisile, O., Cai, D., Oluwasanmi, A., Ejiyi, C., Ukwuoma, C. C., Ojo, O., Mukhtar, M., & Huang, Q. (2022). Comprehensive assessment, review, and comparison of AI models for solar irradiance prediction based on different time/estimation intervals. *Scientific Reports, 12,* 9644. https://doi.org/10.1038/s41598-022-13652-w

Bansal, V., Agarwal, M., and Verma, J. (2025). Transformative applications of artificial intelligence in ophthalmology: A review on eye disease detection. *International Journal for Scientific Research & Development, 12*(11), 76–80. https://www.ijsrd.com/articles/IJSRDV12I110041.pdf

Casado-Moreno, J., Masia, B., Lu, N., Cui, L., & Consejo, A. (2025). Deep learning-based keratoconus detection from Scheimpflug images. *Biomedical Optics Express, 16*(8), 3047-3060. https://doi.org/10.1364/BOE.559663

Cleveland Clinic. (2024, February, 5). *Eye diseases.* https://my.clevelandclinic.org/health/diseases/eye-diseases

eHealth4Everyone PhD Team. (2023, November). *Ethical considerations in AI data science: The Health Data Analytics Research Fellowship Programme.* eHealth4Everyone. https://ehealth4everyone.com/ethical-considerations-in-ai-and-data-science/

Federal Government of Nigeria. (2023). Nigeria Data Protection Act, 2023. *Federal Republic of Nigeria Official Gazette, 110(119), A719-A758.* https://assets.kpmg.com/content/dam/kpmg/ng/pdf/nigeria-data-protection-act2023.pdf

Gill, H. S., Khalaf, O. I., Alotaibi, Y., Alghamdi, S., & Alassery, F. (2022). Multi-model CNN-RNN-LSTM based fruit recognition and classification. *Intelligent Automation & Soft Computing, 33*, 637-650. https://doi.org/10.32604/iasc.2022.022589

Hamid, S. A., Hasan, M. M., Rahman, F., Abdulmajeed, S. M., & Chowdhury, I. H. (2024). Parental eye care-seeking behavior and knowledge of common eye diseases. *The Pan-American Journal of Ophthalmology, 0*, 0. https://doi.org/10.4103/pajo.pajo_100_2

Han, J.-H. (2022). Artificial intelligence in eye disease: Recent developments, applications, and surveys. *Diagnostics, 12*(8), 1927. https://doi.org/10.3390/diagnostics12081927

Harti, M. E., Andaloussi, S. J., & Ouchetto, O. (2025). A Comprehensive Review Comparing Artificial Intelligence and Clinical Diagnostic Approaches for Dry Eye Disease. *Diagnostics, 15*(23), 3071. https://doi.org/10.3390/diagnostics15233071

He, T., Zhou, Q., & Zou, Y. (2022). Automatic detection of age-related macular degeneration based on deep learning and local outlier factor algorithm. *Diagnostics, 12*(2), 532. https://doi.org/10.3390/diagnostics12020532

Hirani, R., Noruzi, K., Khuram, H., Hussaini, A. S., Aifuwa, E. I., Ely, K. E., Lewis, J. M., Gabr, A. E., Smiley, A., Tiwari, R. K., & Etienne, M. (2024). Artificial intelligence and healthcare: A journey through history, present innovations, and future possibilities. *Life, 14*(5), 557. https://doi.org/10.3390/life14050557

Jayan, J. (2024). *Importance of ethical data collection.* PromptCloud. https://www.promptcloud.com/blog/improtanceofethicaldatacollection

Kamińska, A., Pinkas, J., Wrześniewska-Wal, I., Ostrowski, J., & Jankowski, M. (2023). Awareness of common eye diseases and their risk factors: A nationwide cross-sectional survey among adults in Poland. *International Journal of Environmental Research and Public Health, 20*(4), 3594. https://doi.org/10.3390/ijerph20043594

Kavianfar, A., Salimi, M., & Taherkhani, H. (2021). A review of the management of eye diseases using artificial intelligence, machine learning, and deep learning in conjunction with recent research on eye health problems. *Journal of Ophthalmic and Optometric Sciences, 5*(2), 57-72. https://doi.org/10.22037/joos.v5i2.39708

Kim, J., Tran, L., Peto, T., & Chew, E. Y. (2022). Identifying those at risk of glaucoma: A deep learning approach for optic disc and cup segmentation and their boundary analysis. *Diagnostics, 12*(5), 1063. https://doi.org/10.3390/diagnostics12051063

Li, Z., Wang, L., Wu, X., Jiang, J., Qiang, W., Xie, H., Zhou, H., Wu, S., Shao, Y., & Chen, W. (2023). Artificial intelligence in ophthalmology: The path to the real-world clinic. *Cell Reports Medicine, 4*(7), 101095. https://doi.org/10.1016/j.xcrm.2023.101095

Odeyemi, C. S., Olaniyan, O. M., Sobowale, A. A., & Samuel, I. B. (2024). Artificial intelligence (AI) based techniques for reducing neonatal mortality in Nigeria: A descriptive review. *UNIOSUN Journal of Engineering and Environmental Sciences, 6*(2). https://doi.org/10.36108/ujees/4202.60.0280

Okokpujie, K., Adekoya, T., Orimogunje, A., Mommoh, J., Ijeh, A., & Ogundele, M. (2025). Development of a web-based application for real-time eye disease classification system using artificial intelligence. *International Journal of Reconfigurable and Embedded Systems, 14,* 558. https://doi.org/10.11591/ijres.v14.i2.pp558-574

Priyadharshini, G. M. E., Balananthakumar, B., & Jancy, M. (2026). AI-enabled eye screening tool for early detection of common eye diseases. *International Journal of Advanced Research in Computer and Communication Engineering.* https://doi.org/10.17148/IJARCCE.2026.15556

Raut, P., Babar, S. Patil, S., & Mahalle, P. (2024). Machine Learning-Based Detection and Classification of Eye Diseases: A Comprehensive Review and Novel Algorithm. *International Journal of Intelligent Systems and*

Applications in Engineering, 12(13s), 622–629. https://ijisae.org/index.php/IJISAE/article/view/4627

Safaa, M. M. (2023). Diabetes Mellitus Control and Chronic Kidney Disease. *American Journal of Chemistry and Pharmacy, 2*(2), 9-14. https://doi.org/10.54536/ajcp.v2i2.1612

Shimu, F. S., Sajj, A. B., & Sharmin, T. (2025). Associated Systemic Risk Factors and Neuro-imaging Findings of Unilateral Optic Disc Swelling in a Bangladeshi Population. *American Journal of Medical Science and Innovation, 4*(2), 73-77. https://doi.org/10.54536/ajmsi.v4i2.5742

Skipper Eye-Q International Eye Hospitals (SEIEH) (2023, October 23). *What is the prevalence of eye problems in Nigeria?* https://skippereyeq.com/what-is-the-prevalence-of-eye-problems-in-nigeria/

Weni, I., Utomo, P. E. P., Hutabarat, B. F., & Alfalah, M. (2021). Detection of cataract based on image features using convolutional neural networks. I*ndonesian Journal of Computing and Cybernetics Systems, 15*(1), 75-86. https://doi.org/10.22146/ijccs.61882

World Health Organization. (2019, October 8). *World report on vision*. World Health Organization. https://www.who.int/publications/i/item/world-report-on-vision

World Health Organization. (2026, February 10). *Blindness and vision impairment*. https://www.who.int/news-room/fact-sheets/detail/blindness-and-visual-impairment

Yin, S., Wang, L., Wu, S., Jiang, J., Qiang, W., Wang, Y., Wang, S., Shao, Y., Chen, W., & Li, Z. (2025). Mainstream artificial intelligence technologies in contemporary ophthalmology. *Advanced Intelligent Systems, 7*(12), https://doi.org/10.1002/aisy.202500055