

Clinical Evaluation of Early Screening and Diagnostic Methods for Refractive Errors in Children



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Abstract

Introduction: One sort of visual issue that impairs vision clarity is refractive errors. It occurs when an eye's morphology prevents light from properly concentrating on the retina. Predicting a child's refractive error with accuracy is essential for identifying amblyopia, a condition that can cause irreversible vision loss but may be treated if caught early.

Objective: The most crucial elements for effective screening are a precise prediction algorithm and simple access to photo screening applications.

Method: In this study, we proposed a novel Kookaburra-optimized lightweight dense convolutional neural network (KO-LDCNN) to forecast children's refractive error range. We are utilizing data from eccentric photorefractive images that were taken using a smartphone. Using cycloplegic refraction to quantify spherical values, photorefractive images were classified into several groups. The collected data noise

reduction using min-max normalization. It improves the quality and clarity of the images. Data segmentation using Regions of Interest (ROI) involves identifying specific image areas. Subsequent to the segmentation process, the data was extract from the features using linear discriminate analysis (LDA).

Result: The proposed method is compared to the other traditional algorithms. According to these result, our suggested approach work efficiently sufficient to be correct.

Conclusion: The importance of early photo screening intervention in controlling refractive errors and fostering the best possible visual outcomes in children.

Keywords: *Photo Screening, Refractive Errors, Photorefraction Images, Regions of Interest (ROI), Smartphone, Amblyopia, Kookaburra optimized lightweight dense convolutional neural network (KO-LDCNN)*

1. Introduction

Clinical evaluation, which provides necessary information in sequence about the circumstances of a patient, their reaction to therapy, and overall well-being, is the basis of useful healthcare. A clinical evaluation is mostly crucial for early screening and indicative method for child myopic disorder [1]. Particular techniques counting autorefraction, visual acuity testing, retinoscopy, and ocular health assessment are part of the clinical assessment practice for pediatric eye care. These approaches are tailored to the stage of development and level of support of young patients to detect refractive issue early on, supply suitable treatment, and ensure optimal visual outcome [2]. Clinical assessment must be precise and complete for the regimen to be effective. For this reason, clinical consideration is a crucial tool for pediatric ophthalmologists and healthcare administrators in general. Since myopia maculopathy, a disorder in which detached retinas cause and persistent vision loss carries such a high risk of everlasting loss of vision, it has been labeled a serious worldwide health concern. It is well known that the percentage of people with severe myopia increases with increasing onset age [3]. Consequently, using a myopia preventive approach is essential to lessen or postpone the earliest signs of myopia. In addition to refractive abnormalities, strabismus, and anisometropia are other visual issues that can hinder a child's normal growth of vision. These changes are a frequent reason for either unilateral or bilateral loss of vision associated with an eye disease [4]. Amblyopia caused by refractive problems can occasionally be treated with glasses. To prevent vision problems in children and enhance the quality of life for adults, early detection and management of refractive imperfections and the condition were essential. Since childhood eye issues usually don't have any symptoms, they often go organic and receive incorrect conduct. Schools

must regulate vision screening programs during a child's growing period to guard against potential harms at school brought by untreated refractive defects [5]. Somewhat more than identifying or treating degrees, such eye tests aim to promptly identify refractive defects or vision issues [6]. By using these diagnostic measures, healthcare providers could more effectively diagnose, treat, and monitor children's refractive issues, ultimately contributing to the greatest possible visual health and wellness [7]. To accurately assess a child's visual acuity and identify refractive irregularities in situations of refractive errors, a range of specialized methods are employed in the diagnostic process. The primary screening technique for astigmatism, hyperopia, and myopia is visual acuity screening, which uses standardized eye charts. Autorefraction offers computerized estimates of refractive errors, while retinoscopy provides a human evaluation that is particularly useful for younger children [8]. Cycloplegic refraction gives events that are more precise since the edition is uninvolved by completely freezing the ocular muscle. Ocular health examination, in addition to corrective exams, detects the original medical environment that may affect vision [9]. These screening techniques, which are tailored to the unique needs and stage of growth conversant by every child, are central for the early detection, accurate diagnosis, and competent dealing that ultimately support the optimal state of visual health and console in children and adolescents [10]. The aim of this study is to expand and evaluate a precise prediction approach for the spectrum of refractive errors among kids whose smartphone-captured eccentric photorefraction pictures are used. The method employs a novel Kookaburra-optimized lightweight dense convolutional neural network (KO-LDCNN).

Contributions of the study

- Making use of min-max normalization to reduce noise in the gathered data, improving the clarity and quality of the images.
- A lightweight convolutional neural network with Kookaburra optimization was particularly created to use photorefraction photos to predict children's refractive defects.
- The screening technique for early diagnosis of refractive problems is made more accessible and convenient by utilizing eccentric photorefraction pictures taken with cell phones.

The study is organized as follows: section II lists relevant works; section III outlines the recommended methodology; section IV addresses the findings and section V wraps up the conclusion.

2. Related Works

When doing close tasks, convergent insufficiency (CI) [11] common monocular vision impairment, frequently produces symptoms. It was uncertain, yet, which screening test was optimal for CI. This study set out to determine if standard measures of compensatory and binocular function might reliably identify kids who have CI in a school screen context [12]. These digital technologies, which tackle COVID-19 and other difficulties, comprise artificial intelligence (AI), the Internet of Things (IoT), and fifth-generation (5G) telecommunication networks [13]. Together, they form an interrelated system that presents prospects for the development of new healthcare systems. Most nations with low or middle incomes do not include red reflex test (RRT) screening in the routine examination that precedes the newborn's release from the hospital. Examining RRT's diagnostic reliability in identifying neonatal ocular anomalies was the main goal of this research. The clinical investigations from the Age-Related Eye Disease Study (AREDS) [14] and the UK Biobank provided the 45 and 30-degree field of vision retinal fundus images utilized in the present research. The refractive error was quantified using AREDS's subjective refract and UK Biobank's autorefraction. The development of machines such as graphics processing devices, advancements in mathematical models, and the accessibility of large datasets have made it possible for AI [15] to get dependable outcomes for a variety of social network applications, the web, the Internet of Things (IoT), the automotive sector, and healthcare. AI used machine learning (ML) and deep learning (DL) methods. The present and ongoing advancements in the field of nanomaterial-based sensors allow for the detection of volatile organic compounds (VOCs) [16] expelled from one or more human tissues and bodily fluids, allowing quick, reasonably priced, and barely (or non-) intrusive diagnostics in diseases with monitoring. It assessed Peek Acuity's capacity to recognize kids with accessible ocular problems and contrasted visual acuity evaluations amongst approaches using the intraclass correlation coefficient (ICC) [17]. The bounds for agreement from Bland-Altman analysis, severity among differences, and the intraclass ICC [18] were the statistical metrics used to determine the interexaminer repeatability and consistency with the highest level of confidence. Astronauts experiencing extended periods of gravity exposures in long-duration spaceflight (LDSF) exhibited peculiar neuro-ophthalmic physiological and pathological characteristics. The "Spaceflight Associated Neuro-ocular Syndrome" (SANS) [19] was defined by the results linked to spaceflight. When compared to a match in age, developing controls, those with autism spectrum disorder (ASD) had considerably less accommodating replies and hip accommodation was linked to a decrease in near visual acuity (NVA) [20] and converged. Nine to fourteen-year-olds were asked to take part. The convergent A lack of symptom survey, modified thorington, accommodating magnitude, accommodating facility, near point of convergence (NPC) [21] and strong fusional vergences were examined. Using the community, the purpose of the research was to present the minimal test battery required to screen for

non-strabismic binocular vision abnormalities (NSBVAs) [22]. When screening a large number of people without the option for a more thorough and laborious clinical evaluation, finding the best test batteries was the goal that had to be achieved. When doing routine Retinopathy of Prematurity (ROP) screenings [23], retinal pictures were taken on a cohort of prematurely born newborns utilizing RetinaScope. Two masked graders evaluated the images to assess the quality of the images, whether additional disease was present or not, and if the retinal disease satisfied the established referral criteria. Medical professionals and researchers are currently focusing on the less studied eye areas associated with the anterior layer of the retina because of recent advances and interest confirmation of AI [24] in the discipline of eye care, especially about retinal conditions and conditions such as term.

3. Methodology

Several crucial procedures are involved in the clinical assessment of early screening and diagnostic techniques for refractive problems in pediatric patients. Before identifying current screening and diagnostic methods, a thorough literature research is carried out. The research then selects a cohort of kids in a given age range. Figure 1 depicts the flow of the methodology.

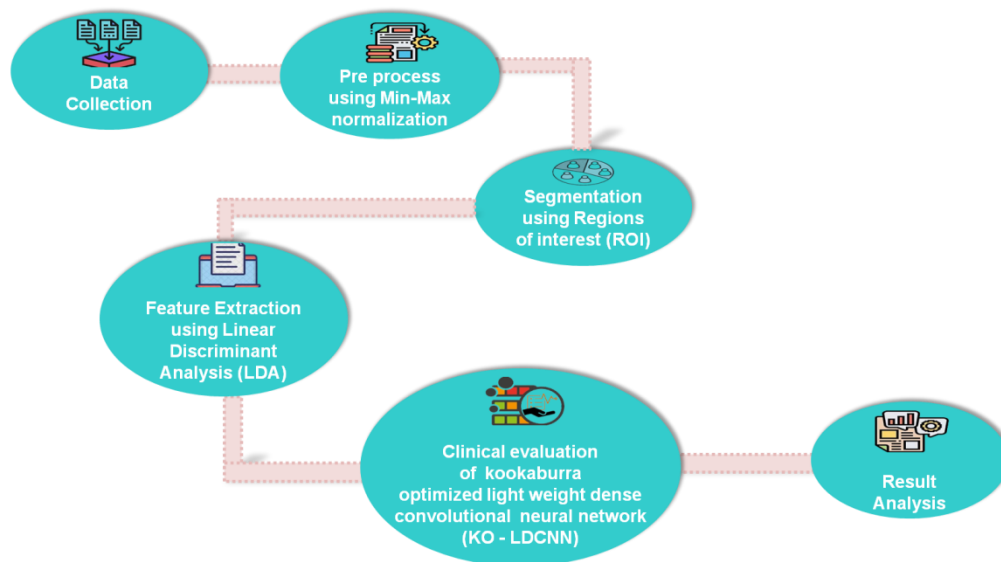


Figure 1: Flow of proposed

3.1. Dataset

A section presents research that used 150 photorefractive pictures taken of kids who were about 8 years old. The photos were captured with a smartphone that has a 16-megapixel camera in a poorly lit area. A testing set of 20% and a training set of 80% of the data were separated for analysis. The images were taken before administering eye drops for cycloplegic retinoscopy. The spherical values obtained during the refraction were then used to categorize the pictures into seven groups, which ranged from high myopia to high hyperopia.

3.2. Data preprocessing using the Min-Max normalization

To give a similar set of values before and after the procedure, a normalization technique known as max-min normalization makes linear changes to the original data.

$$Y_{\text{new}} = \frac{Y - \min(Y)}{\max(Y) - \min(Y)} \quad (1)$$

Y_{new} = The accustomed worth obtained after scaling the data

Y = outdated value

$\text{Max}(Y)$ = Maximum value acceptable for the dataset

$\text{Min}(Y)$ = Minimum possible value in the dataset.

3.3. Data segmentation using Regions of Interest (ROI)

ROI identification in early screening and diagnostic methods for refractive errors in children using the limited quadrant division process that follows is used to identify ROI. Using similarity metrics, we compare the left quadrant of the top and bottom halves to their corresponding right quadrants. Each left sub-quadrant mean is then compared to the corresponding half of the right sub-quadrant in evaluating early screening and diagnostic methods for refractive errors in children clinically. ROI was extracted during the segmentation stage in the clinical evaluation of early screening and diagnostic procedures for children's refractive mistakes using quad analysis to evaluate the effectiveness of these methods for refractive errors in pediatric patients. Clinical evaluation has been balanced between early screening and diagnostic methods for refractive errors in children.

3.4. Feature Extraction using Linear Discriminant Analysis (LDA)

After the segmentation, the study used Linear Discriminant Analysis (LDA) to extract the features. This method is based on the assumption that the probability distribution of each class is Gaussian (normal). In addition to assuming normalcy, the LDA depends on establishing a priori probability. This work will use the subsequent approach. By using the Bayes rule, each sample is allocated to the group that has the highest prior chance. This indicates that each portion is specific to the class j that produces the most irrelevant value of D_j below the guess above.

$$D_j = (y_i - \mu_j)^T \Sigma^{-1} (x_i - \mu_j) + \log|\Sigma| - 2\log(\pi_i) \quad (2)$$

Where μ_j indicates the class income and Σ of course, the inconsistency matrix shared by all kinds is referred to as the group. This requirement applies to all Mahalanobis distances for which the previous likelihood is the same across any class. It is necessary to compute the average matrix and correlation using the information provided. Typically, the grouping resources y_i is used to establish the resources. The next estimate Σ is frequently for the expected covariance matrix:

$$T = \sum_{j=1}^j \frac{(M_j-1)S_j}{(M-j)} \quad (3)$$

Where S_j is the class j empirical variance-covariance matrix. A major flaw with LDA is that it requires a matrix of covariance that is well-conditioned. According to this, the strategy is inappropriate when there are few variables, populations that include more than one component, or substantial correlations between any two of them.

3.5. Early Screening and Diagnostic of Refractive Errors in Children using Kookaburra optimized lightweight dense convolutional neural network (KO-LDCNN)

The Kookaburra Optimized Lightweight Dense Convolutional Neural Network (KO-LDCNN) can be a specific kind of deep learning design made to be efficient with computing power while achieving outstanding results in computer vision applications like recognizing images and groups.

3.5.1 Lightweight dense convolutional neural network (LDCNN)

Lightweight dense CNN aims to reduce the amount of the variables and calculations without sacrificing the effectiveness of existing models, enabling the use of on handheld devices with limited power and storage space. Due to its success in minimizing processing and parameter counts by utilizing shared

weights and sparse connections, CNN is frequently utilized in image analysis. Nevertheless, its applicability in handheld devices is restricted by two factors: model memory and prediction of model speed.

Dense Unit: DenseNet creates a dense block by joining dense cells two at a time. This section describes residual connections and the general topology of the network, as well as three features of the layer of convolution location.

Convolution Layer Placement: The preactivation architecture and the 1×1 combining then the 3×3 convolution pattern are both used by the DenseNet's dense unit. Preactivation is done by the BN and ReLU layers before mixing. Placement of the convolutional layer, which is classified as preactivation or non preactivation and allows ReLU and BN to swap places, improves the density unit (Figure 2a).

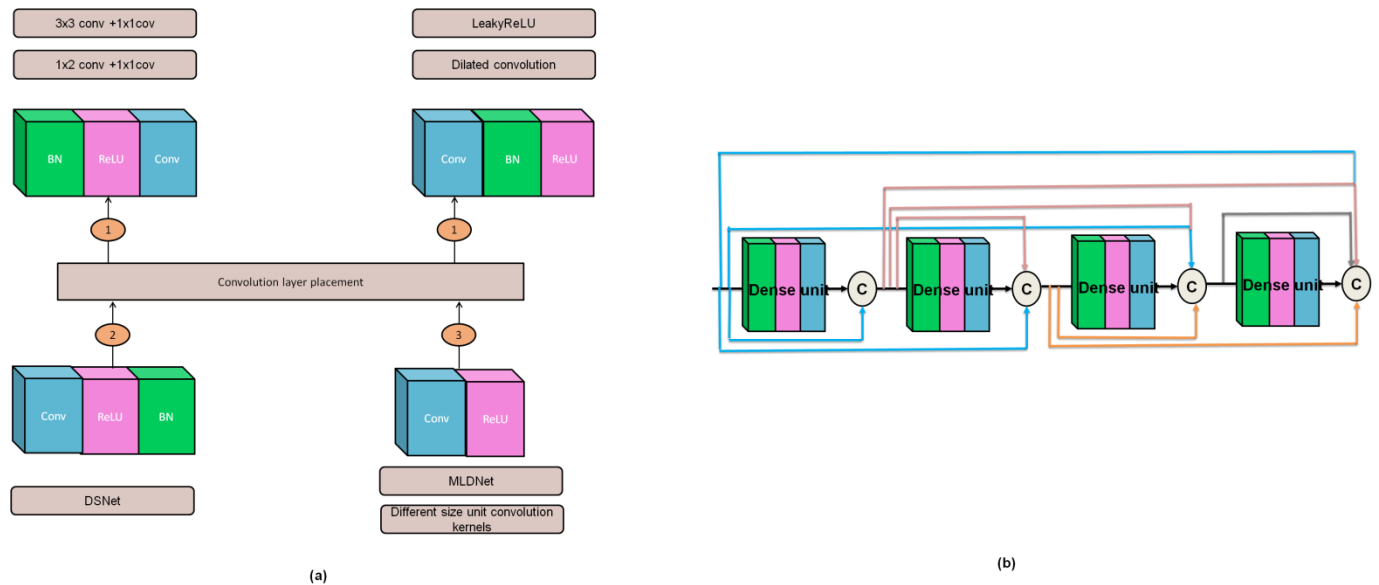


Figure 2: (a) Convolution layer placement (b) Dense link mode

Dense Connection Mode: A dense connection mode offers several characteristics that minimize overfitting and net gradient disappearance while maximizing information flow and lowering variables. All dense units inside a single dense block are linked two at a time using this dense connecting method, as seen in Figure 2 (b). Initially, a dense connection feeds its output into layers that come after it.

Topological Structure: Conventional L -layer CNN has L relations, while DenseNet has $L(L + 1)/2$ relations; densely connected L^{th} layer has L inputs, which, as Figure 3 illustrates, are feature maps of its forebears. It is this two-by-two connected interconnection that gives DenseNet its continuous mapping, deep oversight, and substantial diversity qualities.

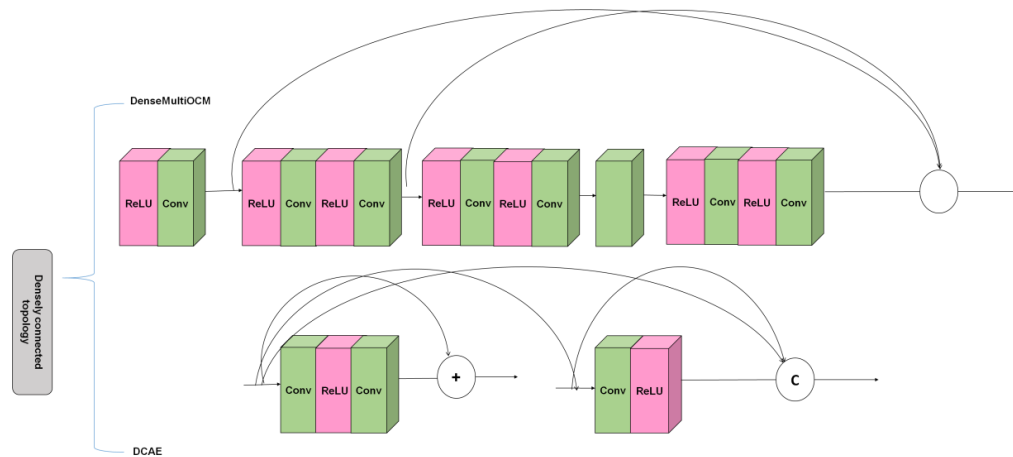


Figure 3: Structure of topologic

DenseNet's Technique for Concentration: Dense blocks and transitional layers constitute the majority of DenseNet. To enhance the transmission of features and reduce the total amount of network parameters, Figure 4 shows how the mechanism for attention is added to DenseNet. Channel, spatial, channels spatial, and residue are the four categories of attention processes seen in dense blocks. By introducing SE to suppress redundant features and emphasize critical features, 3D SE-DenseNet for dynamic upgrading refractive errors in images facilitates the fusing of map features and enhances network performance and accuracy. Using the spatial focus section to encode and decode neglect connection, Att-DenseUnet was able to divide skin lesions with high influence accuracy, clear boundaries, and high recall results. The encoding stage of the model focused on lesion region features by using advanced semantics context data, while the dense block suppressed irrelevant object region features.

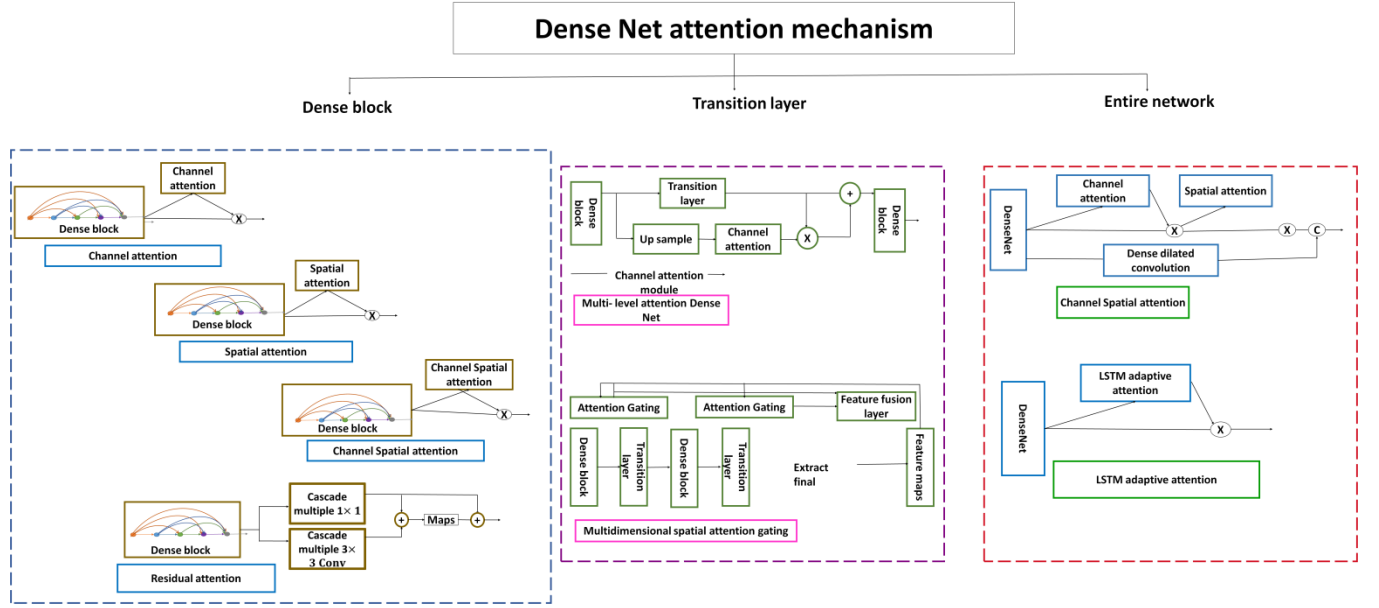


Figure 4: Denset attention mechanism

3.5.2. Kookaburra optimization (KO)

A relative of the terrestrial tree species Coraciiformes and Alcedininae, the carnivorous Kookaburra is part of the Dacelo genus and belongs to the eagle family. The kookaburra's beak is useful for both diving and hunting. The method used by the kookaburra in its natural hunt behavior, which involves slamming its victim against trees to guarantee its death, is far more important than any other behavior.

Initialization: The suggested KOA technique is based on population optimization that uses a random search in the solving problems space to produce appropriate solutions for optimization issues in a process of iteration. Equation (4) could be used to represent the KOA population matrix, which is made up of these animals together. Equation (5) is used to randomly initialize the kookaburras' location at the start of the KOA execution.

$$W = \begin{bmatrix} W_1 \\ \vdots \\ W_j \\ \vdots \\ W_M \end{bmatrix}_{M \times n} = \begin{bmatrix} W_{1,1} & \dots & W_{1,c} & \dots & W_{1,n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ W_{j,1} & \dots & W_{j,c} & \dots & W_{j,n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ W_{M,1} & \dots & W_{M,c} & \dots & W_{M,n} \end{bmatrix}_{M \times n} \quad (4)$$

$$w_{j,d} = Ja_c + q \cdot (va_c - Ja_c) \quad (5)$$

Here, W is the KOA population matrix, W_j is the j^{th} kookaburra, W_{jc} is its j^{th} measurement in the hunt room, M is the numeral of kookaburras, n is the numeral of choice variables, q is a chance numeral in time $[0,1]$, Ja_c and va_c are the inferior jump and higher jump of the j^{th} . Each kookaburra's position in the issue-solving galaxy offers a potential resolution for the current problem associated with that kookaburra, which can be utilized to assess the problem's objectivity. According to equation (6), a vector may be considered to represent the set of examined outcomes for the problem's function's objective.

$$E = \begin{bmatrix} E_1 \\ \vdots \\ E_j \\ \vdots \\ E_M \end{bmatrix}_{M \times 1} = \begin{bmatrix} E(W_1) \\ \vdots \\ E(W_j) \\ \vdots \\ E(W_M) \end{bmatrix}_{M \times 1} \quad (6)$$

Here, E is the vector of the evaluate point occupation and E_j is the evaluate point purpose base on the j^{th} kookaburra. A useful metric for assessing the calibre of population members and feasible options is the assessed values of the intended functionality. The individual who attains the highest judged worth for the objective functions is deemed most successful; conversely, the member with a lowest evaluated value for the function that is objective is least effective.

Mathematical Modelling of KOA: To develop possible remedies based on mathematical modeling of real-world kookaburra behaviors, the suggested KOA technique updates kookaburra positions in two phases: exploration and exploitation. This is done through an iterative process. We then go over how the KOA populace is updated inside the search space.

Phase 1: Hunting Strategy: Kookaburras are carnivorous birds that eat mice, frogs, bugs, vertebrates, and other small birds. The robust neck of this bird aids in its hunting, even if its legs are feeble. These animals produce significant displacement in their location as a result of their prey selection and assault methods. This technique uses the concept of investigation to represent a global search, which is related to the careful scanning of the solving issues space to avoid becoming caught in the neighborhood ideal to identify the primary optimum region. Equation (7) therefore determines the available food set for each Kookaburra, accounting for the variances within the function's value objectives.

$$DO_j = \{W_l: E_l < E_j \text{ and } l \neq j\}, \text{ where } j = 1, 2, \dots, M \text{ and } l \in \{1, 2, \dots, M\} \quad (7)$$

Here, DO_j is the put of entrant victim for j^{th} kookaburra, W_l is the Kookaburra that outperforms the j^{th} kook in terms of the object purpose worth. To identify the kookaburra's new location, the computerized

model of the kookaburra's arrival to the prey in the seeking method is fitted with equation (8). In this instance, equation (9) demonstrates that the new position of the associated kook is going to replace the place of the old site if the amount of the variable targeted grows elsewhere.

$$w_{j,c}^{01} = w_{j,c} + q \cdot (SCP_{j,c} - J \cdot w_{j,c}), j = 1, 2, \dots, M, \text{ and } c = 1, 2, \dots, n \quad (8)$$

$$W_j = \begin{cases} W_j^{01}, & E_j^{01} < E_j \\ W_j, & \text{else} \end{cases} \quad (9)$$

Here $w_{j,c}^{01}$ is the revised i th kookaburra planned position based on the first stage of the KOA, $w_{j,c}^{01}$ is its c th width, E_j^{01} is its value as a mathematical function, q is an arbitrary number in the interval [0,1] that has a normal distribution, $SCP_{j,c}$ is the j th measurement of chosen prey for j th kookaburra, j is a casual numeral from set {1,2}, M is the numeral of the kookaburra, and n is the numeral of the factor used in the choice.

Phase 2: Making Certain the Victim Is Slain: After assaulting their prey, the kook carries the victim with it and ensures that it dies by repeatedly striking it against trees. Kookaburras exhibit this behavior near their hunting grounds, which causes little shifts in their location. This procedure, which embodies the idea of exploitation in local search, speaks to the algorithm's capacity to provide superior results close to regions of promise and already-obtained answers. Equation (10) is used to determine a random location in the KOA design, it mimics how kookaburras strength act based on how far they go in relation to their territories for hunting. In actuality, it is believed that this shift has a radius equal to $(\text{max} - \text{min})$. The previous position is replaced if the new location found for each kookaburra increases the numerical value of the objective variable, as per equation (11).

$$w_{j,c}^{01} = w_{j,c} + (1 - 2q) \cdot \frac{(va_c - Ja_c)}{s}, j = 1, 2, \dots, M, c = 1, 2, \dots, n \quad (10)$$

$$W_j = \begin{cases} W_j^{02}, & E_j^{02} < E_j \\ W_j, & \text{else} \end{cases} \quad (11)$$

W_j^{02} is the revised location of the kookaburra, as suggested by the subsequent KOA phase, $W_{j,c}^{02}$ is its c th measurement, E_j^{02} is Its importance as an objective variable, i is the algorithm's repetition countertop, which indicates the greatest number of repeats.

Our technique is unique as we have created and implemented a Kookaburra-optimized lightweight dense convolutional neural network (KO-LDCNN) that is intended for early screening and diagnosis of refractive problems in children. Our model offers a smooth and user-friendly approach for precise refractive error range prediction by utilizing deep learning to analyze eccentric photorefraction photos taken with cellphones, in contrast to traditional methods. By utilizing sophisticated methods such as linear discriminant analysis (LDA) in conjunction with ROI segmentation and min-max normalization for noise reduction, our approach achieves better accuracy in prediction than conventional algorithms by guaranteeing improved image quality, correct data segmentation, and effective feature extraction. These innovative techniques not only streamline the screening procedure but also highlight how dangerous early interference is in fixing refractive errors and caring for kids' vision.

4. Result

Clinical evaluation studies regarding early screening and testing for refractive errors in children have established their efficiency in quickly diagnosing and scheming diseases, including hyperopia, myopia, and astigmatism. These studies show how examination is effective in detecting a refractive issue, which reduces the possibility of amblyopia and enhances the visual outcome. The experiments took place using a PC wine waiter outfitted with an Intel Compassion i7-7700 HQ CPU @ 2.80 GHz processor, 16 GB of RAM and a 6 GB Nvidia GeForce 1060 graphics certification. For comparative analysis of the proposed method in this study, we used existing techniques, such as Multilayer Perceptron (MLP) [25], Decision Tree (DT) [25], Random Forest (RF) [25], and Support Vector Machine (SVM) [25].

ROC Curve: The diagnostic potential of binary classifier systems when its ability to differentiate threshold is changed is shown graphically by a Receiver Operating Characteristic (ROC) curve. To comprehend and illustrate the trade-off between specificity and sensitivity, it is frequently used to binary classification issues. This is due to the algorithm's current ability to distinguish two distinct binary groups with the least degree of overlap. Figure 5 shows the ROC. Table 1 depicts the outcomes of the existing and proposed method.

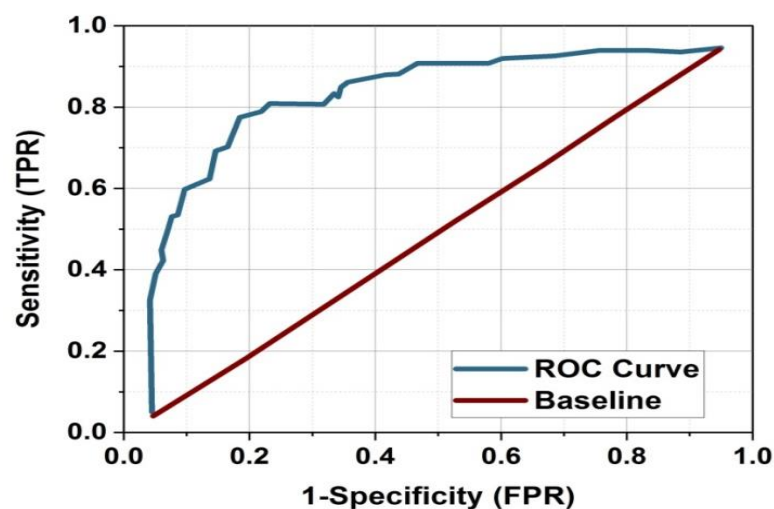


Figure 5: Result of ROC

Table 1: Outcomes of existing and proposed methods

Methods	Accuracy	Precision	Recall	F1-Score
MLP	0.905	0.91	0.90	0.87
DT	0.944	0.79	0.83	0.81
RF	0.981	0.86	0.88	0.85
SVM	0.976	0.74	0.86	0.79
KO-LDCNN [Proposed]	0.984	0.95	0.96	0.89

Accuracy: The accuracy of the model was defined as its percentage of correct predictions. It turned out to be accurate and it was only a small portion of the approach forecasts. Figure 6 shows the outcomes of accuracy.

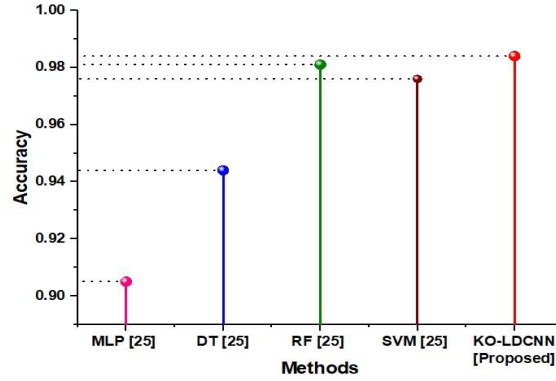


Figure 6: Analysis of accuracy

MLP [25] provided 0.905, DT [25] provided 0.944, RF [25] provided 0.981, and SVM [25] provided 0.976 therefore our proposed technique was greater than the current methods when contrasting the accuracy of our recommended approach, KO-LDCNN [Proposed], which has achieved 0.984.

Precision: Precision is a frequently utilized outcome variable, especially in classification tasks. A model that determines the total number of optimistic forecasts generated by the example determines the number of actual positive predictions. Figure 7 shows the outcomes of precision.

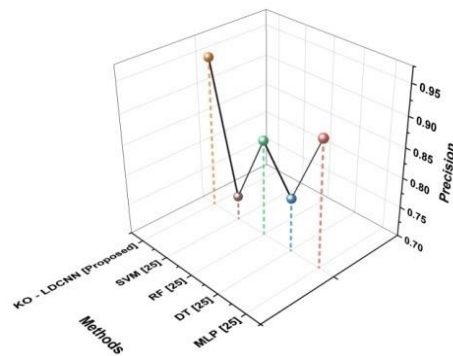


Figure 7: Analysis of precision

In contrast to the prevailing methodologies, the newly introduced KO-LDCNN demonstrated a significantly enhanced precision of 0.95. Among the current approaches, MLP [25] attained an precision of 0.91, DT [25] showcased a performance of 0.79, RF [25] showcased a performance of 0.86, and SVM [25] attained an precision of 0.74.

Recall: Recall, often referred to as sensitive positive rate, is an essential indicator of recital in deep learning, especially for classification tasks. It determines the percentage of precise positive forecasts out of all real instances of optimism in the data set. The sum of all correctly predicted positive outcomes is divided by the sum of all wrongly anticipated negative results to determine the recall score. Figure 8 shows the findings of recall.

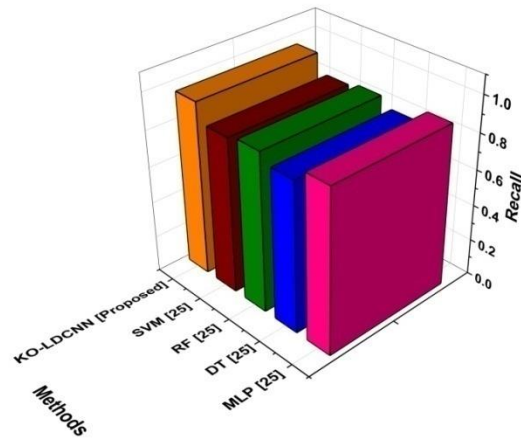


Figure 8: Analysis of recall

In contrast to the prevailing methodologies, the proposed KO-LDCNN exhibited a notably higher recall rate of 0.96. Among the prevalent techniques, MLP [25] attained an recall of 0.90, and DT [25] attained a performance level of 0.83. RF [25] attained an recall of 0.88 and SVM [25] attained a performance level of 0.86.

F1 score: A popular statistic for binary classification tasks, such as assessing how well machine learning models perform, is the F1 score. It provides a single indicator of a model's accuracy by combining recall and precision. Figure 9 shows the outcomes of the F1 score.

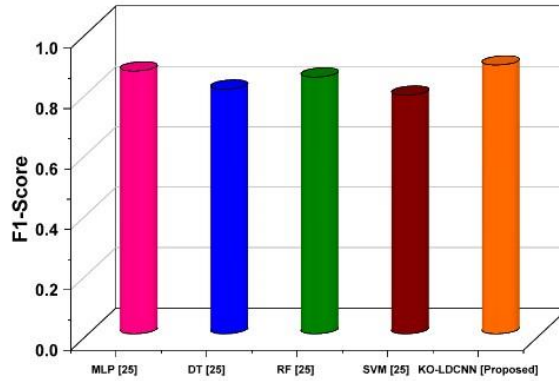


Figure 9: Analysis of F1 score

In contrast to the prevailing methodologies, the newly introduced KO-LDCNN demonstrated a significantly enhanced F1 score of 0.89. Among the current approaches, MLP [25] attained an F1 score of 0.87, DT [25] showcased a performance of 0.81, RF [25] showcased a performance of 0.85, and SVM [25] attained an F1 score of 0.79.

4.1. Discussion

Overfitting of the training data is a common problem with multilayer perceptrons (MLPs), particularly when improper regularization is undertaken. The poor generalization of overfitting to fresh, unseen data is the consequence. To prevent excessive fitting and learn efficiently, MLP [25] usually needs a lot of labeled training data. Since DT [25] tends to favor every class, they do not perform well with unbalanced datasets. The minority group may suffer from low prediction performance as a result. RF [25] can, however, over-fit; even though they are often less likely to do so than single decision trees, particularly when there are a lot of trees or the model is quite complicated. SVM [25] can encounter issues with extremely imbalanced datasets when the total number of instances of one class far outweighs the number of cases of another class. Limits on decisions that are skewed in favor of the dominant class may result from this. We propose KO-LDCNN as a solution to these problems.

5. Conclusion

This study's findings demonstrated that our deep learning-based system produced precise and accurate refractive readings. This highlights the possibility of leveraging deep learning with a massive database of pediatric photo refraction photos from patients with a range of ages and refractive defects to create more

straightforward smartphone-based predictive models for refractive errors. When contrasted with the current approaches, the recommended strategy produced outstanding results in terms of accuracy (0.984), precision (0.95), recall (0.96), and F1 score (0.89). Refractive imperfections can be treated early to improve visual outcomes and lessen the incidence and severity of amblyopia in youngsters. Some screening methods require active cooperation from the child, which cannot always be possible, especially in very young or developmentally challenged individuals. Determine whether early detection and treatment during critical developmental stages result in better visual outcomes compared to interventions initiated later in childhood.

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