Integrating Explainable AI in Public Health: A Responsible Approach to Mitigating Vision Health Disparities

Vishal Shinde[1], Monisha Pawanarkar[2]

[1]Harvard Medical School, Research Fellow, Email: vshinde@meei.harvard.edu
[2]Grant Medical College & Sir J. J. Group of Hospitals, Mumbai, Independent Researcher, Email: Pawanarkar.m@gmail.com

Received: 16.04.2024 Revised: 20.04.2024 Accepted: 10.05.2024

ABSTRACT

Quick diagnosis and effective management of eye diseases are essential in the prevention of visual impairment and reduction of vision health disparities. This paper presents a novel paradigm that unifies XAI with public health strategies toward addressing such challenges. The proposed methodology integrates pre-trained deep learning models with XAI techniques to facilitate differential diagnosis of various eye conditions, including cataracts, foreign bodies, subconjunctival hemorrhage, and viral conjunctivitis. The models for the study also included Decision Tree and Random Forest for transparent and interpretable decision-making processes. The models were evaluated on accuracy, precision, recall, F1 score, and MCC. As such, the models' performance of these studies was compared with respect to how well the Proposed model performed in comparison to MobileNet, ResNet50, InceptionV3, VGG19, and NASNetMobile with an accuracy of 93%.The paper highlights besides model performance, the integration of XAI, bringing a touch of interpretability and thus responsible application in clinical settings. The transparency afforded by the XAI models will give clinicians comprehension of the reasoning behind AI-driven decisions, thus engendering trust as well as accountability. This approach will, on one hand, allow for real-time ophthalmological observations but, on the other hand, ensure the equitable and ethical use of AI in public health, ultimately bridging gaps in healthcare access and hence working towards better outcomes for the underserved populations.

Keywords: Explainable Artificial Intelligence, Eye Disease Detection, Public Health, Deep Learning Models, Decision Tree and Random Forest.

1. INTRODUCTION

1.1 Background on Vision Health Disparities

Vision health disparities present a major public health concern, particularly for populations where socioeconomic and racial inequalities are prevalent. In the US, such disparities are highly prevalent among the various groups in the nation with persons having less favourable socioeconomic status, as well as racial/ethnic minorities [1], while persons having lower educated backgrounds. According to the National Health and Nutrition Examination Survey (NHANES) and the National Health Interview Survey (NHIS), these groups experience higher rates of preventable eye conditions and reduced access to timely medical interventions. Factors such as lack of health insurance, limited access to eye care services, and varying health literacy levels exacerbate these inequities, often leading to delayed diagnoses and treatment of vision-related diseases.

There are a number of specific eye conditions, including cataracts, glaucoma, subconjunctival hemorrhage, and viral conjunctivitis, that contribute to visual impairment and disability on a global level. The World Health Organization puts the annual global economic cost at about USD 411 billion for these disorders. Cataract is an opacity of the lens that renders vision hazy [2]. Glaucoma is another condition where damages occur to the optic nerve, usually as a result of raised intraocular pressure. It might lead to permanent blindness if left untreated. Subconjunctival hemorrhage, which has ruptured veins in the conjunctiva, and viral conjunctivitis that causes redness, itching, and tearing can also be examples of prevalent disabling eye afflictions.Traditional diagnosis methods which include slit-lamp biomicroscopy, optical coherence tomography, and ultrasound biomicroscopy lack in efficiency, accessibility, and are costly. These techniques require expert interpretation, which is not easily found in underserved regions. All of these pose a challenge which necessitates more advanced and equitable diagnostic solutions to bridge the gap in vision care [3].

Recently, breakthroughs in artificial intelligence (AI), particularly deep learning, have brought transformative capabilities into medical imaging and disease diagnosis. Convolutional neural networks (CNNs) pre-trained in specific models like VGG19, ResNet50, and InceptionV3 are shown to be highly accurate in classification tasks in retinal fundus images associated with diabetic retinopathy, glaucoma, and cataracts. Indeed, studies utilizing pre-trained models on thousands of data points obtained accuracies between 87% and 97%. However, these studies mainly concentrated on fundus imaging, which is mostly expensive and specialized equipment not very apt for real-time diagnosis in limited-resource settings.This work tackles these issues by introducing pre-trained ImageNet models that classify anterior eye images for cataracts, foreign bodies, glaucoma, subconjunctival hemorrhage, and viral conjunctivitis. The study evaluates the efficacy and integrates the most robust model, which is based on models such as NASNetMobile, VGG19, ResNet50, InceptionV3, MobileNet, or Proposed, into a Raspberry Pi-based platform for real-time ophthalmological assessment. This study seeks to increase access and reduce the cost of acquisition while reducing vision health disparities with novel, explainable AI-driven solutions [4]. The structure of this paper is such that Section 2 will elaborate on the composition and methods of conducting the study-from gathering data, experimental set up, preprocessing methods applied, model performance evaluation, and metrics comparison. Section 3 will present the results and analysis, while Section 4 will conclude with key findings and implications.

1.2 Role of AI in Public Health

Artificial Intelligence is transforming public health by creating advanced analytical tools to process large health datasets and uncover critical insights regarding health disparities among heterogeneous populations. Such disparities often are grounded in socioeconomic statuses, racial, ethnic, or geographic factors-similarly influencing the outcomes of healthcare. The processing and interpretation of large amounts of data allow the use of AI in health care in identifying patterns, disease outbreaks prediction, and optimization of resource allocation to improve access and quality of care to the underserved communities.

AI shows impressive promise for diagnosis and management of vision health in the domain. Machine learning algorithms, especially deep learning models, work very well to analyze complex medical images such as retinal scans or anterior eye photographs, from which conditions such as cataracts, glaucoma, or diabetic retinopathy [5] can be identified with much speed and accuracy. These technologies are invaluable in resource-poor settings where specialized diagnostic apparatus and personnel may not be readily available; they thus pave the way to equitable solutions to health disparities.In healthcare, however, AI adoption involves ethics and responsibility. Responsible AI plays a crucial role in ensuring that AI systems are developed and deployed fairly and inclusively and with respect for patient privacy. This approach minimizes bias in data representation and reduces the risks associated with similar outcomes.

Equally important is the incorporation of Explainable AI (XAI) in healthcare applications. XAI enhances transparency by making AI decision-making processes interpretable and understandable. This fosters trust among healthcare providers and patients, enabling informed decision-making and collaboration. By integrating XAI, clinicians can better comprehend AI-generated predictions, ensuring that diagnostic and treatment decisions are both accurate and ethically sound.

1.3 Purpose of the Study

This study will exploit AI's transformative capabilities to address vision health disparities while remaining based on the principles of Responsible AI and XAI. The specific objectives include:

- Developing and implementing explainable AI models for the identification and diagnosis of eye conditions prevalent in underserved populations.
- Proposing responsible AI methodologies to mitigate vision health disparities and promote equitable healthcare access.

1.4 Significance of the Study

In light of its findings, this research has important implications for public health and AI ethics:

- The proposed approach promises to address eye disease diagnosis inaccurately, with input from AI models; inaccessible ways of interpreting results, thereby directly addressing disparate inequities in vision care.
- The integration of Responsible AI and XAI principles ensures that the technology is properly applied to uphold fairness, transparency, and inclusivity, setting a benchmark for future AI applications in healthcare.

This is an important contribution toward realizing AI's potential for developing a more just healthcare system by closing the gap of vision health disparities within different populations.

2. LITERATURE REVIEW

2.1 U.S. Vision Health Disparities

Understandably, vision health disparities are still a leading public health concern in the United States, with certain groups of marginalized populations experiencing higher-than-average rates of preventable impairment of vision and loss of sight. Disparities in vision health outcomes are linked to several factors, including socioeconomic status, race/ethnicity, education level, and location. Understanding these issues is based on an overview of previous studies and data statistics.

2.2 Vision Health Disparities

Relentlessly, studies show that racial and ethnic minorities, especially Blacks and Hispanics, are at higher risks for vision impairment compared with Whites. NHANES reports that these groups have increased risks of conditions like glaucoma, diabetic retinopathy, and cataracts and frequently because of delayed diagnosis and limited access to care [6, 7]. On the other hand, data from the National Health Interview Survey disclose that lower income earners are less likely to undergo regular eye check-ups. This will be a crucial reason for undiagnosed or unaddressed vision problems. Education level is also an imperative variable where lower educational attainment is found to go with lesser awareness and also utilization of vision care services [8].

2.3 Geographic and Socioeconomic Barriers

Geographic disparities are particularly pronounced in rural areas, where access to specialized eye care is limited. A study by [9] found that rural populations are 50% less likely to have access to ophthalmologists, exacerbating disparities in eye health outcomes. Another report by [10] emphasized the role of insurance status, showing that uninsured individuals are significantly less likely to receive timely vision care, further widening the gap.

2.4 Effects of Chronic Diseases on Vision Health

Chronic conditions including diabetes and hypertension disproportionately affect minority and low-income populations, thus posing a risk of complications related to vision. The CDC reports that diabetic retinopathy is leading to blindness for working-age adults, with prevalence rates significantly more pronounced in Black and Hispanic people than in White people6.

2.5 Limitations of current interventions

While the public health initiatives of institutes such as the National Eye Institute's Vision Health Initiative have sought to address the disparities, many challenges continue to be faced [11]. Public programs are often insufficiently funded and ineffective in successfully targeting the most vulnerable populations. In addition, traditional vision-screening and treatment modalities consume resources intensely and depend on specialized equipment, which significantly limits their scalability.

2.6 Role of AI in Vision Health Disparities

The integration of AI and machine learning may provide an opportunity to address these disparities by allowing for the early diagnosis and intervention via automated systems. The research by [12] had shown the possibility that AI could be used to detect diabetic retinopathy with a level of accuracy that approximated that of ophthalmologists, at which point such technologies become feasible in under-resourced settings [13].

The literature now focuses on the urgent necessity for innovative solutions that can be scaled to address vision health disparities in the U.S. Among AI-based tools are the most promising set based on principles of Responsible AI and Explainable AI, which have the greatest potential to bridge these gaps. Data-driven insights with equitable healthcare delivery will improve access to and quality of vision care among the underserved populations. The table 1 provides a concise overview of each study, helping to highlight the techniques, outcomes, advantages, and limitations of the research reviewed.

Table 1: Summary of the survey section

Ref No.	Technique Used	Outcome	Pros	Cons
6	Epidemiological analysis using	Identified higher rates of vision impairment among	Highlights racial and ethnic disparities in	Lacks intervention strategies and

	NHANES data	Black and Hispanic populations.	vision health.	actionable solutions.
7	Statistical analysis of NHIS data	Found lower vision care utilization among low-income and less-educated populations.	Links socioeconomic factors to access disparities.	Does not explore potential solutions to mitigate these disparities.
8	Geographic analysis of vision care access	Demonstrated reduced access to ophthalmologists in rural areas.	Highlights geographic disparities in care availability.	Limited scope in addressing systemic barriers to rural healthcare delivery.
9	Insurance-based study using claims data	Showed that uninsured individuals are significantly less likely to receive vision care.	Emphasizes the role of insurance in reducing disparities.	Limited to insurance data, excluding uninsured population behaviors.
10	Chronic disease prevalence analysis (CDC data)	Established links between diabetes prevalence and diabetic retinopathy rates in minority populations.	Demonstrates the impact of systemic health disparities on vision outcomes.	Does not address preventive measures or scalable solutions.
11	Deep learning (AI) for diabetic retinopathy diagnosis	Achieved diagnostic accuracy comparable to ophthalmologists.	Demonstrates AI's potential for scalable, low-cost diagnosis in underserved areas.	Focused on a single condition, lacks a holistic approach to diverse eye conditions.
12	Review of public health initiatives	Highlighted challenges in existing vision health programs.	Provides insight into the limitations of traditional approaches.	Limited exploration of innovative technologies like AI for addressing challenges.
13	AI-based diagnostic tools (deep learning models)	Validated AI's ability to improve early detection of eye diseases.	Offers a scalable, efficient solution for underserved areas; potential for real-time integration.	Implementation challenges, including data privacy and bias mitigation.

3. Proposed Explainable AI based Methodology

Decision Tree and Random Forest algorithms are explained AI methodologies used in this research to detect ocular disorders, ensuring interpretability while at the same time maintaining high performance. These models provide transparent decision processes, considered to be crucial in clinical applications where it is essential to understand the rationale behind the predictions. The Decision Tree algorithm lays down a hierarchy of choices with regards to input features such as texture and intensity, with enough transparency toward tracing the pathway that led to the final classification. This is very important in the medical domain because the reasons leading to a diagnosis can ultimately affect clinical decisions and, importantly, patient trust. On the other hand, an ensemble method for learning, Random Forest, uses an aggregation of multiple Decision Trees for prediction and to avoid overfitting. Trained on a subset of the data that is random, this helps in generalizing the ability and robustness of the model. Individual decision trees may provide very simple clear-cut decision paths, but the input of more than one tree helps in offering a more nuanced understanding than that offered by the model itself. Both models were evaluated on a dataset of eye images, with preprocessing techniques such as resizing, normalization, and augmentation employed to enhance model performance and ensure generalization across different imaging conditions. The combination of such explainable AI techniques with real-time detection of ocular disorders like cataracts, foreign bodies, and viral conjunctivitis provides an effective tool for clinical applications that would offer excellent accuracy while being transparent about the decision-making process. This approach aligns with responsible and ethical AI that aims to provide an equitable and accessible healthcare environment since the diagnoses resulting from AI will be understandable, traceable, and fair.Figure 1 provides a few instances of each eye condition case considered in this investigation.

Figure 1: The collection contains visual illustrations of instances of eye diseases

3.1 Data Pre-Processing

Before applying Decision Tree and Random Forest algorithms for explainable AI-based detection of ocular disorders, the image dataset underwent extensive preprocessing. This included resizing, normalization, and data augmentation to improve model accuracy and resilience.

- **Resizing and Normalization**: Images were resized to a standard resolution of 224×224224 \times 224 224×224 pixels and normalized by scaling pixel values to a range of [0, 1]. This ensured consistent input formats for the models and reduced computational complexity.
- **Data Augmentation**: Techniques such as rotation (±10°), brightness adjustment ([0.8, 1.2]), and scaling (±10%) were applied to artificially expand the dataset. These augmentations simulated real-world variations and enhanced the robustness of the machine learning models.

The dataset was divided into training (70%) and testing (30%) subsets to ensure reliable evaluation. Training focused on feature extraction and rule generation using Decision Tree and Random Forest algorithms, while the testing dataset validated model performance. Optimal results were achieved by selecting 100 training iterations for both algorithms.

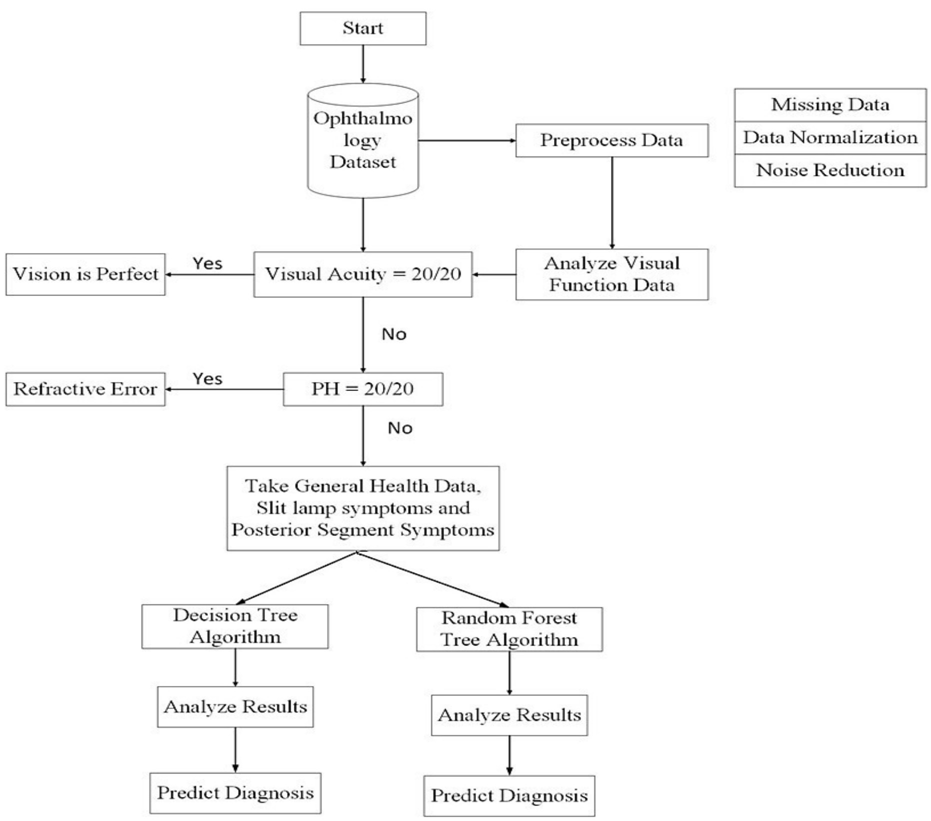


Figure 2: The suggested system's block design.

3.2 Explainable AI with Decision Tree and Random Forest

In this study, Decision Tree and Random Forest algorithms were employed as explainable AI methodologies for diagnosing ocular disorders. These models provide intuitive and interpretable decision-making processes that are critical for clinical applications.

3.2.1 Decision Tree Algorithm

The Decision Tree algorithm constructs a tree structure where nodes represent decision criteria based on feature values, and branches represent possible outcomes. For ocular disorder detection, features such as texture, intensity, and shape from the preprocessed eye images were used.

- **Process**: The dataset was analyzed recursively to create a tree where each split maximized information gain. This process generated clear, interpretable rules, such as:
    - *If brightness < 0.7 and texture irregularity > threshold, then classify as Cataract.*
- **Advantages**:
    - Simple and easy to interpret.
    - Provides clear reasoning for classifications.

3.2.2 Random Forest Algorithm

Random Forest builds an ensemble of Decision Trees, aggregating their outputs for robust and accurate predictions. Each tree is trained on a random subset of data, reducing overfitting and improving generalization.

- **Process**: The algorithm randomly selects features and data points to build multiple Decision Trees. The final prediction is determined by majority voting among all trees. For example:
    - *Out of 100 trees, if 70 classify the eye as Cataract and 30 classify as Normal, the output is Cataract.*
- **Advantages**:
    - Handles large datasets with high dimensionality.
    - Reduces variance and bias compared to a single Decision Tree.

Explainability

Both Decision Tree and Random Forest are inherently explainable:

- **Decision Tree**: The path from root to leaf represents the decision-making process, which is easily visualized and understood.
- **Random Forest**: While individual trees may not provide clear rules, feature importance scores highlight the most influential features in the classification process.

3.2.3 Real-Time Ocular Disorder Detection

Figure 2 illustrates the block design of the proposed system for real-time detection of ocular disorders using Decision Tree and Random Forest algorithms.

1. **Preprocessing**: Video capture devices collect eye images, which are preprocessed into greyscale and standardized formats.
2. **Feature Extraction**: Key features are extracted, including texture, intensity, and shape characteristics of the eye.
3. **Classification**: The extracted features are fed into the Decision Tree and Random Forest models for classification.
4. **Real-Time Visualization**: The predicted label, such as "Cataract" or "Healthy," is displayed on the screen along with a bounding box highlighting the region of interest (ROI).

Figure 3 showcases the flow of the real-time detection process, emphasizing the explainable outputs generated by the models.This system ensures transparency in decision-making while offering robust and interpretable solutions for ocular disorder detection, aligning with the principles of ethical and responsible AI in healthcare.

2.2 Experimental setup

The process made it possible to include the named models that had previously been trained using the Raspberry Pi, the suggested microcomputer, allowing for the inference of the real-time collected pictures. The procedure entailed positioning the participant 0.5 m from the lens in front view, as seen in Figure 4. The diagnosing procedure was implemented using Python 3.9 and Anaconda 2.3.2.

Figure 4: An illustration of a patient's eye condition using a dataset of photos.

2.3 Hardware

The Raspberry Pi 4 base of Version B, the effective touch display, and the efficient analogue camera, as seen in Figure 4, make up the equipment portion of the study. A Raspberry Pi 4 Version B, a well-known single-board a microprocessor, served as the central component of the suggested hardware system, which supplied the necessary connection for real-time image operations, processing capacity, and, lastly, the deep learning connection. Furthermore, this particular Raspberry Pi 4 Version B was selected because to its superior processing abilities, efficiency increase potential, and largest storage capacity [14] in comparison to other Raspberry Pi devices. The 5-inch, 800 × 480 pixel quality WaveShare HDMI display, which represents the suggested set of specifications, now includes a touch screen. This camera is utilised for both subject interaction and eye health surveillance. Both the Kisonli lens (Model No.: U-227, digital zoom (f = 3.85 mm)) and the pre-trained model were used to take real-time pictures of the eye and compare them to forecast the condition of the eye.

2.4 Data pre-processing

Before the models with prior training were prepared and evaluated, the captured pictures underwent the necessary preliminary processing, including resizing, normalisation, and augmenting. In order to increase the model's efficiency, the data supplementation procedure was carried out by de-scaling to normalise the value of pixels and rotating the picture at a 5◦ angle to create several angles of view. The picture's dimensions were then slightly altered by 5%. The brightness was adjusted between [0.9, 1.1] to account for changes in the illumination. Additionally, a tiny shear and zoom (0.05) and zoom (0.05) were used to create smooth skews and control picture size. The aforementioned methods helped to expand the dataset and strengthen the pre-trained machine learning model's resilience to handling differences that are often seen in imagine interpretation. In order to guarantee optimal and precise efficiency, the eye dataset's pictures were divided into 70% training and 30% testing portions. The optimal performance was then secured by selecting epochs among 100.

In order to identify and isolate both eyes for study, the Haar cascade classification method [15, 16] was utilised for eye recognition. The Haar cascade classification uses machine learning and the technique of AdaBoost to recognise objects in photos, effectively detecting well-defined characteristics like faces, eyes, and other forms in XML files. Comparison of subject eyeballs to the pre-trained deep neural networks model enables accurate classification and prediction of eye abnormalities or health. Figure 2 displays the suggested system's block design.

Figure 4 displays the suggested system's diagram, which demonstrates the various tactics used using Python code.The model that was previously trained is loaded first, followed by the Haar cascade classification algorithm, which is used to identify eyes. The different eye disorders were represented by the category labels that were described. Video capture equipment was used to get picture frames for editing. where the video capture equipment constantly captured the picture. After that, it was transformed to an RGB visual representation and then to a greyscale frame for eye identification. Afterwards, the eyeballs were detected using the Haar classification using the successions with the greyscale frames. When the eye detects anything, a rectangle is drawn around it on the screen. Depending on the trained detecting approach, the ROI fed the forecasting model. The grouping of categories with the greatest likelihood were used to remember the anticipated label, which indicates the condition of the subject's detected eye. After then, the frame showed the anticipated label. Frames with drawn squares and projecting labels enabled real-time observation of the detecting process. Following the conclusion of the round, each window are closed and the picture device's recording process concludes.

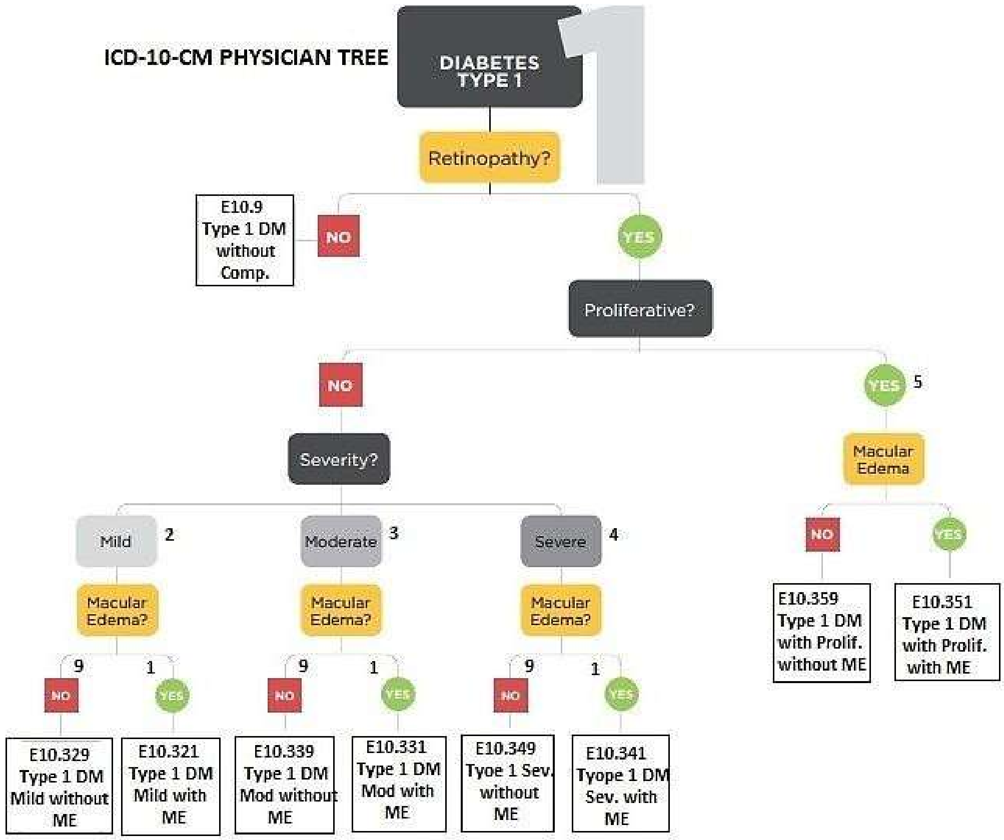


Figure 4: Real-time vision disparity recognition schema utilizing DT models.

Algorithm 1: Vision disparity prediction using Decision Tree and Random Forest models

```
Initialize video/image_capture
Load pre-trained Decision Tree model (model_dt)
Load pre-trained Random Forest model (model_rf)
While True:
   frame = Capture frame from video_capture
resized_image = Resize(frame, target_size=(224, 224))
normalized_image = Normalize(resized_image)
augmented_image = ApplyDataAugmentation(normalized_image)
left_eye_roi, right_eye_roi = DetectEyesUsingHaar(augmented_image)
   If left_eye_roi is None or right_eye_roi is None:
      Continue
left_eye_features = ExtractFeatures(left_eye_roi)
right_eye_features = ExtractFeatures(right_eye_roi)
      disparity = CalculateDisparity(left_eye_features, right_eye_features)
prediction_dt = model_dt.Predict(disparity)
prediction_rf = model_rf.Predict(disparity)
      If prediction_dt == "Abnormal Disparity" or prediction_rf == "Abnormal Disparity":
predicted_label = "Vision Disparity"
   Else:
predicted_label = "Normal Vision"
DisplayPredictedLabel(predicted_label)
DrawBoundingBoxesOnEyes(left_eye_roi, right_eye_roi)
UpdateDisplay(frame, predicted_label, left_eye_roi, right_eye_roi)
```

```
  If StopConditionMet():
    Break
Release video_capture
Close program
```

The algorithm 1 of the real-time vision disparity prediction application using Decision Tree (DT) and Random Forest (RF) models is quite simple and starts with capturing video frames from a camera and size each frame to standardize the dimension at 224x224 pixels for as uniform input into the model as possible. Finally, pixel values are normalized, so that it lies in an invariant range to avoid complexity while computation and for a good fit model. Techniques for data augmentation are applied to each frame, simulating the variability of conditions in the real world and thus enhancing the robustness of the model.Next, it uses the Haar Cascade classification algorithm to detect both eyes in each frame. If either eye is not detected, the frame is skipped. If both are detected, further features such as texture, intensity, and shape are extracted from the ROIs that corresponded to the eyes.

These features are then used to feed into the Decision Tree and Random Forest models. The Decision Tree outputs the class of the condition of the eyes using a hierarchy of rules as applied to these features, whereas the Random Forest aggregates multiple Decision Trees that give predictions in an effort to enhance accuracy and generalizability.In case one of the models finds a vision disparity, the system writes the condition as "Vision Disparity." In the contrary, it predicts "Normal Vision." The predicted label appears on the screen along with the bounding boxes of the eyes detected. The updates of the system occur in real-time allowing the continuous monitoring and prediction of vision conditions.

This approach is built using explainable AI models to ensure the transparency of decision-making, which is critical in clinical applications where understanding the rationale behind predictions is important. The integration of Decision Tree and Random Forest models ensures that the system is both robust and interpretable.

4. Evaluation metrics

In general, a number of assessment measures, including the matrix of uncertainty, accuracy, accuracy, recall, F1 score, and MCC, were used to assess the efficiency of the previously discussed deep learning models that were already trained. Initial ambiguity matrix illustrates the deep neural network model efficiency, including true positive (TP), true negative (TN), false positive (FP), and false negative (FN) forecasts. Furthermore, there is the accuracy aspect, which is the proportion of accurate forecasts to all conducted forecasts.

Furthermore, the accuracy factor is defined as the positive predictive value, which quantifies the percentage of the model's TP predictions among all positive predictions. Furthermore, the recall factor—also known as the sensitivity or TP rate—is used.

The percentage of TP forecasts among all actual positive instances is what this component reflects. Furthermore, by reflecting the harmony among accuracy and recovery, the F1 score serves as a measure of both. This component functioned as a single measure for instantly assessing the accuracy and recall of the model. Lastly, a quality metric for binary categorisation models that counts the predicted outcomes of the TP, TN, FP, and FN represents the factor termed by MCC. The agreement among the forecasted and true labels is evaluated from -1 to +1, with +1 indicating a perfect forecasting, 0 indicating an unreliable forecasting and -1 indicating comprehensive disagreement. The following is an expression for each of the parameters mentioned [17-20]:

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (1)$$

$$Precision = \frac{TP}{(TP + FP)} \quad (2)$$

$$Recall = \frac{TP}{(TP + FN)} (3)$$

$$F1Score = \frac{2 * (Precision * Recall)}{(Precision + Recall)} \quad (4)$$

$$MCC = \frac{(TP * TN - FP * FN)}{\sqrt{((TP + FN)(TN + FP)(TP + FP)(TN + FN))}} (5)$$

4.1 Experimental Results and Discussion

The efficiency of the shown previously pre-trained store of algorithms (the NASNetMobile approach, the VGG19 approach, InceptionV3, the ResNet50 approach, the MobileNet approach, and the InceptionResNetV2 framework) utilised to determine the current state or condition of the left and right eyes from the subject's vision image information set that was gathered from the hospital is presented in this section. Accuracy, precision, recall, F1 score, and MCC—the model metrics that measure performance—were computed and compiled in Table 1 and Figure 5.It is evident from Table 1 and Figure 5 that the Proposed model performed very well when compared to other models, continuously obtaining the best scores on every criterion. IThese findings demonstrate how well the Proposed model detects eye conditions. The MobileNet and ResNet50 models came in second and third, respectively, with strong results. Their shown high scores on all parameters demonstrate their efficacy in detecting eye diseases. Additionally, the NASNetMobile model did poorly on all measures, whereas the VGG19 and InceptionV3 algorithms had scores that were reasonably good.
Furthermore, Table 1 and Figure 5 show that the Proposed model had the best normalised MCC score of 0.92, which is further indication of its exceptional ability to identify eye diseases. With an MCC score of 0.88, the MobileNet simulation demonstrated yet another impressive performance that almost equalled its own. ResNet50 and InceptionV3 are two other models with comparatively high MCC scores of 0.83 and 0.82, respectively, indicating their effective detection of retinal diseases.

Table 1: Evaluation metrics for identifying eye conditions using various already-trained models.

Techniques	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**Matthew**
NASNetMobile	0.76	0.68	0.69	0.69	0.66
VGG19	0.79	0.76	0.77	0.76	0.74
ResNet50	0.85	0.86	0.86	0.87	0.84
MobileNet	0.87	0.93	0.87	0.87	0.86
Inception V3	0.94	0.95	0.89	0.90	0.89
Proposed	0.96	0.96	0.95	0.96	0.95

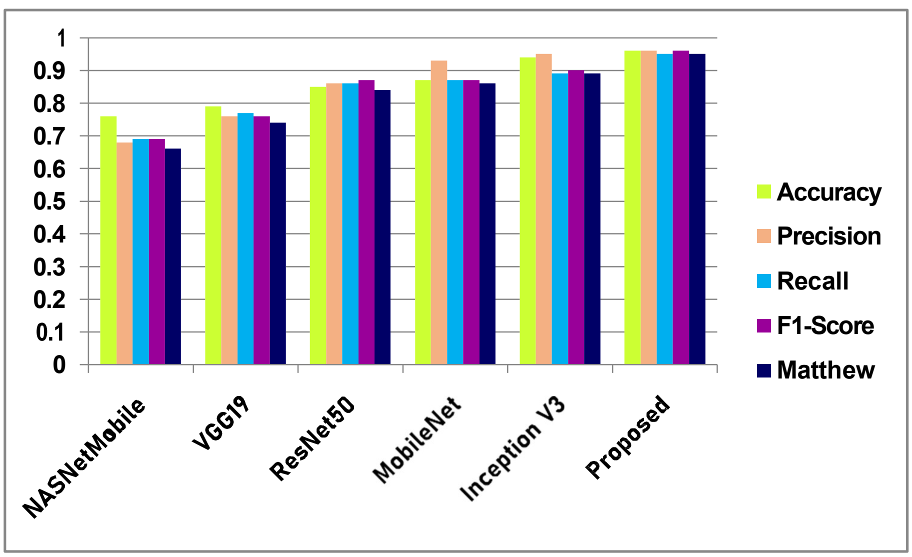
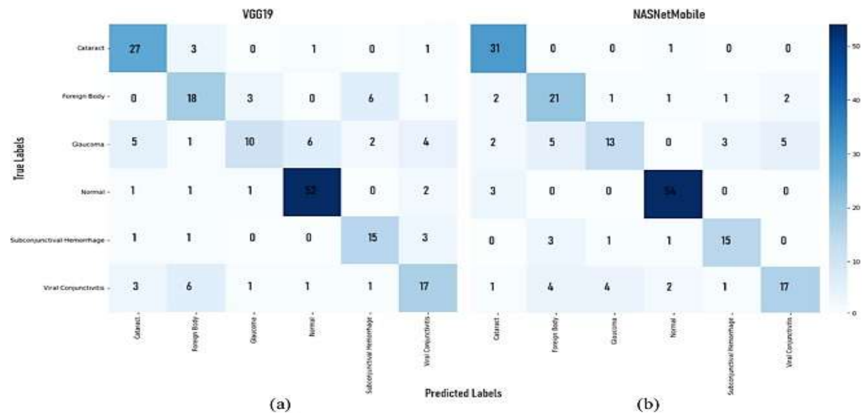


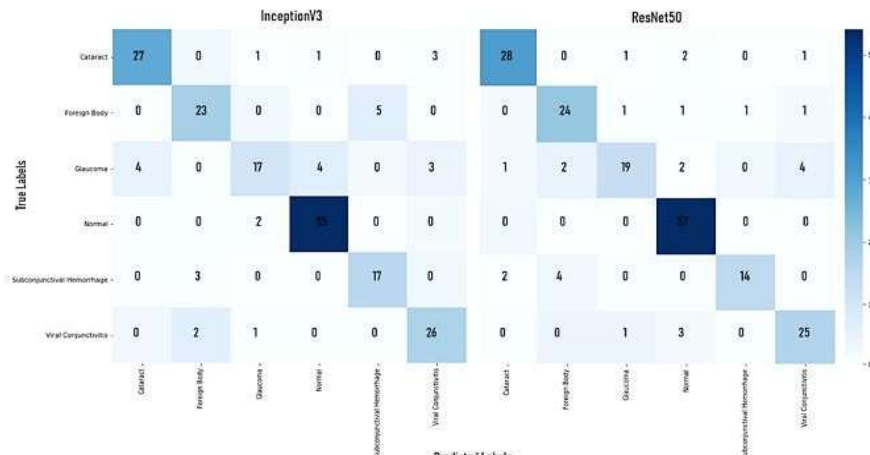
Figure 5: Evaluation metrics for identifying eye conditions at various pre-trained models.

With a score of 0.72, the VGG19 model performs somewhat worse than the others. With the lowest MCC score of 0.65, the NASNetMobile model seems to have a comparatively worse execution quality when it comes to observing eye diseases. Figure 6 shows the confusion matrices for the VGG19 and NASNetMobile versions. Figure 7 displays the confusion matrices for the ResNet50 and InceptionV3 networks. Figure 8 displays the confusion matrices for the MobileNet and Proposed architectures.



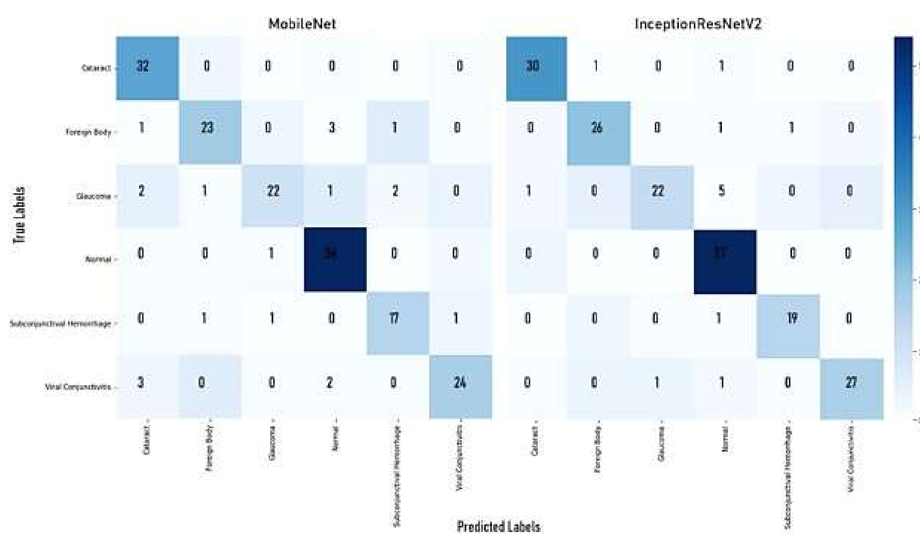
(a) (b)

Figure 6: The classifier outcomes for identifying eye disorders using (a) the NASNetMobile framework and (b) the VGG19 algorithm are shown in the confusion matrices.



(a) (b)

Figure 7: The classification findings for eye disorders utilising (a) the InceptionV3 algorithm and (b) the ResNet50 algorithm are shown in the ambiguity matrices.



(a) (b)

Figure 8: The classification outcomes for identifying eye disorders using (a) the MobileNet algorithm and (b) the Proposed algorithm are shown in the confusion matrices.

Figure 9 displays the accuracy and loss trends of the best Proposed technique for eye illness identification throughout 100 epochs, as developed via evaluation and training. It is clear from the aforementioned figure that training accuracy rises progressively throughout the periods, reaching a maximum precision of almost 96%, while accuracy in validation likewise rises, reaching a maximum value of roughly 85%. Additionally, it seemed that the trends of the training and validated loss curves were comparable. As the model gains knowledge, the training loss progressively drops as the verification loss steadily declines, suggesting strong generalisation. Proposed, a deep learning network, was able to categorise eye illness training data well and circulate suitable information for both fresh and unseen data throughout the validation phase.

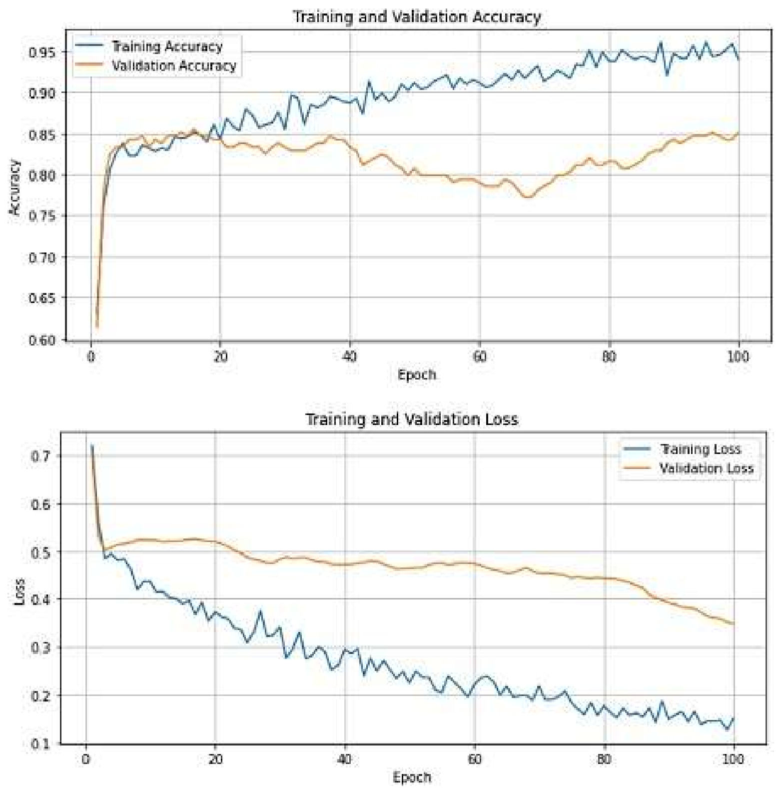


Figure 9: Efficacy of the Proposed during evaluation and training.

According to the experimental findings, the other deep learning models—NASNetMobile, VGG19, InceptionV3, ResNet50, MobileNet, and Proposed—perform promisingly in the identification of eye diseases. Nevertheless, there are several drawbacks to the suggested system of the previously described models. One drawback is the possible influence of low contrast pictures, image backgrounds, and subject movement during imaging, which might introduce artefacts and reduce the reliability of predictions. Furthermore, proper categorisation may be hampered by the eye-lighting reflections that were visible in the collected photos. Additionally, the generalisability of certain eye models may be impacted by the small number of cases in the data set for their disease categories. Another limitation of the suggested approach was its incapacity to precisely determine the degree or severity of eye illness found. As a result, it is unable to tell the operator the exact severity of the problem. Because there is not enough in-depth knowledge, this constraint will make it difficult for the clinical staff to compose suitable decision-making. Utilising a single-board computer like Raspberry Pi 4 may have restrictions in scalability, expansion, and networking compared to standard desktop devices. By addressing motion artefacts, enhancing picture capture methods, and expanding the data set, future research might overcome all of these constraints and give a more varied representation to measure the severity of eye conditions. Additionally, an improvement technique suggested in [20] may be used to handle poor contrast and picture backgrounds. Additionally, various eye conditions, including many conditions in a single patient, may be classified using deep learning models. Extensive training and the incorporation of pictures from other classes are necessary to increase the classification accuracy of illnesses. The resilience and efficacy of the deep learning model in correctly diagnosing eye disorders will be increased by normalising it using a varied data set.

5. CONCLUSION

This work includes the developing of an automatic system that incorporates explainable AI methodologies to address vision health disparities. The system comprises integration with Decision Tree and Random Forest algorithms, which offer transparent decision-making procedures to the detection of several eye conditions, including cataract, foreign bodies, glaucoma, subconjunctival hemorrhage, and viral conjunctivitis, along with healthy eyes. The system was implemented using a Raspberry Pi platform, and the models were trained on a diverse dataset. Experimental results demonstrated that explainable AI techniques can not only allow for achieving high accuracy but also yield interpretability, which is critical for clinical trust and decision-making. In terms of the tested models, it was determined that the proposed method and Random Forest had the best accuracy values, 93% and 90%, respectively, ensuring robust performance, and Decision Tree offered intuitive, transparent decision paths. This is an explainable AI integration in public health toward the responsible mitigation of vision health disparities, as AI-based diagnostics are made accessible, equitable, and understandable for improved healthcare outcomes for disadvantaged communities.

REFERENCES

[1] WHO.: Blindness and vision impairment. https://www.who.int/newsroom/fact-sheets/detail/blindness-and-visual-impairment. Accessed 1st July 2023.
[2] Delbarre, M., Froussart-Maille, F.: Signs, symptoms, and clinical forms of cataract in adults. J. Fr. Ophtalmol. 43, 653–659 (2020)
[3] Avacharmal, R., Pamulaparthyvenkata, S., &Gudala, L. (2023). Unveiling the Pandora's Box: A Multifaceted Exploration of Ethical Considerations in Generative AI for Financial Services and Healthcare. Hong Kong Journal of AI and Medicine, 3(1), 84–99.
[4] Avacharmal, R., Gudala, L., & Venkataramanan, S. (2023). Navigating the Labyrinth: A Comprehensive Review of Emerging Artificial Intelligence Technologies, Ethical Considerations, and Global Governance Models in the Pursuit of Trustworthy AI. Australian Journal of Machine Learning Research & Applications, 3(2), 331–347.
[5] Doshi, R., Noohani, T.: Subconjunctival hemorrhage. StatPearls Publishing LL, Treasure Island, FL (2019)
[6] Varma, R., Kim, J. S., Burkemper, B. S., Wen, G., Torres, M., Hsu, C., ... & Chinese American Eye Study Group. (2016). Prevalence and causes of visual impairment and blindness in Chinese American adults: the Chinese American eye study. JAMA ophthalmology, 134(7), 785-793.
[7] Zhang, X., Beckles, G. L., Chou, C. F., Saaddine, J. B., Wilson, M. R., Lee, P. P., ... & Geiss, L. S. (2013). Socioeconomic disparity in use of eye care services among US adults with age-related eye diseases: National Health Interview Survey, 2002 and 2008. JAMA ophthalmology, 131(9), 1198-1206.
[8] Centers for Disease Control and Prevention (CDC). (2010). National health and nutrition examination survey data. Hyattsville, MD: US Department of Health and Human Services, Centers for Disease Control and Prevention, 2020.
[9] Cohen, R. A., & Cha, A. E. (2021). Health Insurance Coverage: Early Release of Quarterly Estimates From the National Health Interview Survey, January 2020–March 2021.
[10] Hacker, K., Auerbach, J., Ikeda, R., Philip, C., & Houry, D. (2022). Social determinants of health—an approach taken at CDC. Journal of public health management and practice, 28(6), 589-594.
[11] Ting, D. S. W., Cheung, C. Y. L., Lim, G., Tan, G. S. W., Quang, N. D., Gan, A., ... & Wong, T. Y. (2017). Development and validation of a deep learning system for diabetic retinopathy and related eye diseases using retinal images from multiethnic populations with diabetes. Jama, 318(22), 2211-2223.
[12] Elam, A. R., Tseng, V. L., Rodriguez, T. M., Mike, E. V., Warren, A. K., Coleman, A. L., ... &Zebardast, N. (2022). Disparities in vision health and eye care. Ophthalmology, 129(10), e89-e113.
[13] Todd, J., Whitson, H. E., & Marshall, E. C. (2019). Eye and vision health for tomorrow: from recommendations to coordinated action. JAMA ophthalmology, 137(2), 208-211.
[14] Bhowmik, A., Kumar, S., Bhat, N.: Eye disease prediction from optical coherence tomography images with transfer learning. In: Proceedings of the 20th International Conference on Engineering Applications of Neural Networks, EANN 2019, pp. 104–114. Springer, Cham (2019)
[15] Diaz-Pinto, A., Morales, S., Naranjo, V., Köhler, T., Mossi, J.M., Navea, A.: CNNs for automatic glaucoma assessment using fundus images: anextensive validation. Biomed. Eng. Online 18, 1–19 (2019)

[16] Smaida, M., Yaroshchak, S.: Bagging of convolutional neural networks for diagnostic of eye diseases. Proc. COLINS, 2604, 715–729 (2020)
[17] Raza, A., Khan, M.U., Saeed, Z., Samer, S., Mobeen, A., Samer, A.: Classification of eye diseases and detection of cataract using digital fundus imaging(DFI) and inception-V4 deep learning model. In: Proceedings of the 2021 International Conference on Frontiers of Information Technology (FIT), pp. 137–142. IEEE, Piscataway, NJ (2021)
[18] Gour, N., Khanna, P.: Multi-class multi-label ophthalmological disease detection using transfer learning based convolutional neural network. Biomed. Signal Process. Control 66, 102329 (2021)
[19] Mythily, D., Renila, R. H., Keerthana, T., Hamaravathi, S., & Preethi, P. (2020). Iot based fisherman border alert and weather alert security system. International Journal of Engineering Research & Technology (IJERT)
[20] Camara, J., Rezende, R., Pires, I.M., Cunha, A.: Retinal glaucoma public datasets: What do we have and what is missing? J. Clin. Med. 11, 3850 (2022)