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Machine Learning Techniques for Detecting and Forecasting Disorders in Children Using Pupillometry Data

Dhanush Chaluvadi[1], T Deekshith Reddy[2], D V Sai Pavan[3], Boppuru Rudra Prathap[4]

[1, 2, 3, 4] Department of Computer Science and Engineering, CHRIST (Deemed to be University), Bangalore-560074, Karnataka, India
Corresponding author: Boppuru Rudra Prathap
E-Mail: boppuru.prathap@christuniversity.in
Orcid: https://orcid.org/0000-0002-5161-4972

Abstract- Inherited Retinal Diseases is one among the most significant cause for defects in children resulting in blindness among the children. As diseases of this kind require several clinical test patterns which at most times are inefficient and inappropriate and mostly result in acceptance of alternate methods, as sometime even invasive methods are also used. As this requires a different approach in order to be properly tested and taken care of among the children of the younger age groups and is mostly challenging and difficult to work on. This research deals with a chromatic pupillometry based machine learning approach to satisfactorily diagnose this disease with precise accuracy and specific sensitivity. Several machine learning based decision-making support systems such as Support Vector Machine, BiLTSM, Artificial Neural Network and LTSM are used in this project in order to achieve the predetermined accuracy that is precise and through which sensitive results are obtained specifically based on each eye in particular. As the pupillometric data set is being uploaded into the dataset, it is preprocessed, where a particular prediction model is generated and then sent for filtering. It is in this place where all the unwanted and non-correlative data is separated and only the required data is worked upon.

Index Terms- Machine learning, pupillometry, python, retinitis pigmentosa, support vector machine, artificial neural network, long short term memory, bidirectional long short term memory.

I. INTRODUCTION

The most common cause of significant vision loss in youngsters is because of Inherited Retinal Diseases. In Institute Market Economies (1/3000 people), they are frequently the cause of childhood blindness. Diseases of the external retina, such as photoreceptor degeneration (e.g., Retinitis Pigmentosa, Stargardt disease, Cone Dystrophy, Leber Congenital Amaurosis, Choroideremia,, Acromatopsia etc.) and diseases of the internal retina, particularly deterioration of retinal cells called ganglion cell, can be distinguished from IRD (e.g. Primary congenital glaucoma, prominent optic atrophy, Leber optic atrophy). These diseases are characterized by considerable inborn variation, which has been found by more than 200 genes to date, posing a significant obstacle to early and successful diagnosis, and it is thought that the same gene could produce many clinical presentations. Retinal Inherited Diseases are leading cause of serious optical impairment in youngsters. In institute market economies (1/3000 people), they are frequently the cause of childhood blindness. Diseases of the external retina, such as photoreceptor degeneration (e.g., Leber Congenital Amaurosis, Retinitis Pigmentosa, Stargardt dis- ease, Cone Dystrophy, Acromatopsia, Choroideremia, etc.) and diseases of the internal retina, such as deterioration of retinal ganglion cells, can be distinguished from IRD (e.g. congenital glaucoma, prominent optic atrophy, Leber hereditary optic neuropathy).The Both disorders had characterized by considerable genetic variation, which has been identified by more than 200 genes to date, posing a significant obstacle to early and successful diagnosis, and it is thought that the same gene can generate many clinical presentations.

1.1 CURRENT CLINICAL EVALUATION METHODS

IRD clinical trials are typically based on a sophisticated clinical trial pattern, which includes invasive procedures

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that are not necessarily appropriate for babies and young children. Electrophysiological tests, for example, often necessitate paediatric intervention because they provide clinical studies that are highly valuable in detecting internal and exterior retinal infections. The retinal response is affected by sedation, which necessitates a complex field of health care (e.g., operating room, pediatrician, anesthesiologist, dedicated instruments, etc.).

1.2 PUPILLOMETRY

A novel method of assisting IRD identification could be beneficial. In this aspect, a methord has been proposed which is called chromatic pupillometry where the most cru- cial test for assessing the activity of distinct light-sensitive retinal cells and has therefore been demonstrated to be useful in diagnosing retinal abnormalities induced by IRDs, as summarised below. When photoreceptor cells (rods and cones) respond to light, they have instantaneous kinetics and create pupil congestion, but retinal melanopsin- containing retinal Ganglion Cells (ipRGCs) have temporary sensitivity and generate pupil light exposure and persistence. Deceptive flash-field features (90) and adaptive settings (light vs. dark) have been used to examine the related contributions of the three types of receptors (rod, cone, and melanopsin photopigments) in the Pupillary Light Reflex (PLR). For example, introducing high light, long wavelength (red) against the flexible rod compression field offers plone-directed PLR, whereas introducing low light, short (blue) lengths to the black flexible eye predominantly delivers rodmediated PLR. There is a passing student block (rod and cone-mediated) continued by repeated melanopsin congestion which can be ontinued for more than 30s after high light, short wave light is injected into the black flexible eye. offset stimulus Clinical investigations have used long melanopsin-mediated constriction to assess the function of the internal retina. As a result, using chromatic pupil responses to diagnose and monitor disorders affecting the exterior or internal retina could be a new approach of doing so. This study implies that a clinical decision-making support system might be beneficial.

II. LITERATURE REVIEW

In the group with IRD, the X.-F. Huang et al [1] offered the genotype-phenotype link, which contains a novel candidate gene, and discovered 124 genetic abnormalities. The discovery of new genotype-phenotype correlations and the spectrum of mutations has substantially improved our understanding of IRD phenotypic and genotypic heterogeneity, making clinical diagnosis and management of IRD patients easier. The author has put together a panel of 164 known retinal detachment genes, 88 genes, and 32 retinal miRNAs for genomic DNA transcription. This panel was utilized in the NGS for the discharge of 179 patients with IRD who were unrelated. In 99 patients, they discovered 124 pathogenic abnormalities, including 79 new mutations in previously recognised IRD genes. Several genotype-phenotype relationships have also been discovered, including the finding of AHI1 as a new nonsyndromic RP gene.

According to the R. Kardon et al [2], the blue light evoked substantially more student reactions in normal eyes at low power than the red light or the picture light. Passive student attenuation was frequently greater than continuous acceleration, and this difference was more noticeable in low light (100 cd / m (2)) and less noticeable in strong blue light. Children with reduced reactions to blue light in the lower extremities were seen in a patient with cerebral palsy. A student's response to red light stimulation was reduced selectively in a patient with chromatopsia and almost normal visual acuity. Students' reflexes to red and blue light were lost worldwide in a patient with ganglion cell failure due to anterior ischemic optic neuropathy. According to the C. Park et al [3], it took 1 second for melanopsin to produce the right student response after the blue stimulus was removed. The components controlled by the PLR rod and melanopsin are best read in the dark with low and high brightness, respectively. The blue back pushed rod

and melanopsin reactions, allowing the red flame to easily check the cone contribution. In actual practice, patients with few or no donations from sticks and cones can have high melanopsin responses. A. Kawasaki et al [4] as indicated by the creators, understudies with NR2E3-related promotion RP had lower retinal aversion to cloud blue light under typical haziness, which could suggest bar restricting. Male-subordinate understudy reactions were discernible and connected with clinical ailment status in all patients, even those with an unrecorded scotopic elec- troretinogram. In contrast with customary electrophysiology, the chromatic student light reflex can be used to evaluate photoreceptor degeneration over a more extensive range of illness progression. P. Melillo et al [5] The Pupillary responses to chromatic stimuli were significantly different between juvenile RP patients and age-matched healthy controls, according to the scientists. Further-more, pupillary responses could be detected in individuals with ERG responses below the noise level, even if they were lower than in patients with a markedly diminished response. As a result, chromatic pupillometry may be useful in clinical studies to aid in the diagnosis of RP in children and to track the progression of associated retinal degeneration. According to the M. Porumb et al [6], Congestive Heart Failure (CHF) is a significant pathophysiological illness with a high prevalence, high mortality rate, and high ongoing health- care costs, and hence demands better diagnostic approaches. Aside from new research that offers powerful signal processing and machine learning approaches, the capacity to apply Convolutional Neural Network (CNN) methods for automatic CHF detection is mostly disregarded.

S. S. Gao et al [7] The Choriocapillaris, according to the authors, is vital in sustaining metabolic demands in the retina. The use of optical coherence tomography angiography (OCTA) to evaluate choriocapillaris in diseased areas has been proven to be useful. Photographic materials, on the other hand, make it difficult to determine choriocapillaris in degenerative disorders such choroideremia. We present a machine-readable learning strategy for acquiring strong choriocapillaris based on effective professional training, professional level.

E. Iadanza et al [8] Many youngsters go blind as a result of these disorders, according to the authors. Given the range of clinical and genetic variables involved, diagnosing this kind of sickness can be challenging (over 200 genes). A alternative technique is provided by Chromatic Pupillometry, a technology that is increasingly employed to test the exterior once inside retinal function. According to the S. B. Kotsiantis et al [9], supervised machine learning is a search for algorithms that are triggered by external variables, develop common hypotheses, and then make predictions about future situations. That is to say. The purpose of supervised learning is to develop a quick model for the distribution of class labels based on predicted data.

J.A. Alzubi et al [10] Classifier integration approaches, according to the authors, have been an important tool for machine learning research in recent years. The goal of putting together classifier ensembles is to increase the collection's accuracy in comparison to any other person. It is divided into many categories. If the collection's basic dividers do not make errors all at once, it can overcome the shortcomings of the particular divider class. Coalition- based Ensemble Design (CED), a novel technique for a coherent integration design, is suggested and investigated in depth in this paper. While enhancing accuracy, the CED algorithm tries to minimise size and a typical classification mistake.

According to the J. Alzubi et al [11], the present SMAC (Social, Mobile, Analytic, Cloud) techno- logical trend opens the way for a future in which smart gadgets,

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network operations, and big data are all linked. This virtual environment has generated a significant amount of data, which has accelerated the adoption of machine learning solutions and procedures. Computers can replicate and adapt to human behavior thanks to machine learning. The O. A. Alzubi et al[12] suggest and analyses the Consensus-based Merging Approach (CCM), a new method for combining an ensemble of classifiers. The outputs of numerous classifiers are weighted and added together in a single final classification decision, as in most other combination techniques.

According to the P. Sajda et al [13], machine learning allows for the systematic development of complicated, automated algorithms as well as the analysis of high-dimensional and mul- timodal biological data. This study focuses on a number of advancements in the state of the art that have showed promise in terms of improving illness detection, diagnosis, and monitoring. The development of in-depth understanding and theoretical study of essential topics connected to algorithmic architecture and learning theory was crucial. According to the J. A. ALzubi et al [14], accurate lung cancer diagnosis (LCD) is critical for giving prompt therapy to lung failure patients. Artificial Neural Networks, a recently created Machine Learning technology that can be applied to both big and small data sets. The combination of Weight Optimized Neural Networks and Maximum Likelihood Boosting (WONN-MLB) for huge data is investigated in this research. Feature selection and segmentation are the two steps of the proposed technique. To decrease separation time, the combined Newton – Raphsons Maximum probability model and Minimum Redundancy (MLMR) pre-processing is used in the first step to pick essential features.

III. METHODOLOGY

Every Research project has its unique technique for developing outcomes, from brainstorming through prototype delivery. One methodology we used is shown in the figure-1. The approach involves brainstorming a concept, drawing it, then using it to produce a design. 4 Next, correct each step's faults. Design, formulation, and brainstorming all include errors. These mistakes must be fixed to produce a decent design. Most of our research results and corrections were gained by trial-and-error, or hit-and-try. During the implementations of these features, we examined the drawbacks and other obstacles faced by similar applications. We subsequently studied the workings if their systems worked and functioned. It was important to understand the stumbling blocks faced by current systems in order to design a system that can overcome these hitches. We extrapolated the necessary information which formed the foundation for this project. In the case of complex issues that the team was not able to resolve, the team sorted help and suggestions from the faculty in charge.

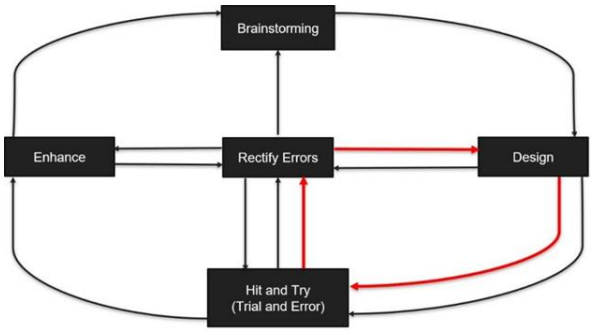

Figure.1 Flow of Research Methodology

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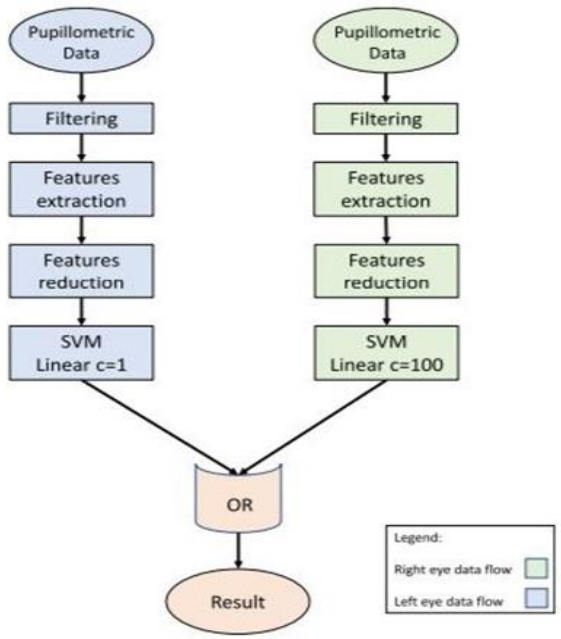

Figure.2 System Architecture Diagram

3.1 PROPOSED SYSTEM

This Research suggested method offers an innovative technique to assisting in the diagnosis of IRDs. In this paper, the architecture of the data acquisition is based upon the data sheets that is being obtained from several sources of internet. This pupillometric data is then conditioned after acquisition is and then sent for filtering where the data the unwanted data is removed which results in proper and precise results. Features from the data are obtained in the process of feature extraction which in this case is done in order to reduce the data dependency which results in faster data processing and faster data outputs as this deals with very large amounts data sets and data as two separate eye related data is recorded for further analysis and obtainment of results for diagnosis. The proposed reseach is developed and designed using SVM,ANN, LSTM and BILSTM. Figure-2 depicts the flow of proposed research methodology with different machine learning algorithms. At the first phase Upload Pupillometry Data using this phase load raw data containing continuous recording of patient data. In the second phase filtering. In this phase raw data contains a large number of buggy values and we will filter that raw data to extract only useful information such as pupil min and diameter size next phase Features Extraction. In this phase all patient features and many are extracted from raw data. Next phase reducing features will remove unnecessary features from raw data such as camera name, position etc to reduce default features. In this phase we extracted features such as Patient ID, MAX, MIN, DELTA, CH etc. Extracted data can be used to classify train and test data.

Next phase is Right SVM will train SVM with relevant patient data. Left SVM will train SVM with patient left data and use SVM for test data to calculate predictive accuracy, sensitivity and precision. Next phase is an Ensemble Algorithm (Left and Right SVM) will combine both the classification schemes to find a divider with high precision prediction. And as final phase as Guess the Disease will load the test data and enter the SVM section to predict the disease.

IV. RESULTS AND ANALYSIS

The sole objective of this research is find IRDs diseases using machine learning algorithm’s and we proposed as novel approach to support the diagnosis of IRDs. The proposed method for diagnosing IRDs is new. This project's data collecting architecture is built on internet-sourced data sheets. After collection, pupillometric data is conditioned and filtered, resulting in exact findings. Feature extraction is done to decrease data reliance, which leads in quicker data processing and faster data outputs as this deals with very big data sets and data as two independent eye related data is collected for subsequent analysis and diagnosis. The project uses SVM,ANN,LSTM,and BILSTM. The following sections will explains the results of the proposed methodology.

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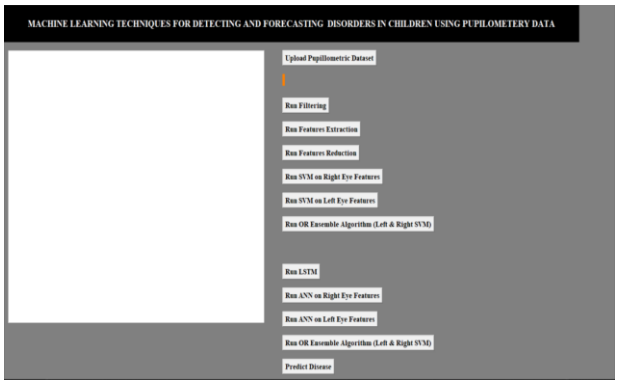

Figure -3 User interface

The figure 3 represents the User Interface of the project, where it consist of different buttons like uploading data set, run filtering,Run features Extraction,Run SVM of left and right eye,Run OR ensemble On both left and right eye.

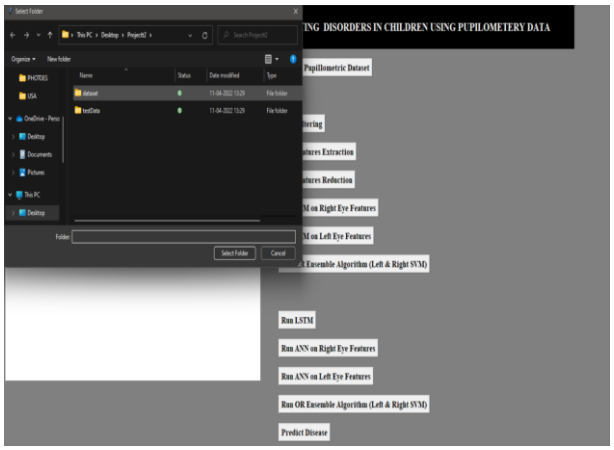

Figure-4 Adding Data Set

The figure 4 depicts how to add the dataset to perform different operations using it. This data set consist of vital patient information regarding the eye which was collect using the pupilometer. The dataset consists of different Parameters like Patient ID,MAX,MIN,DELTA,CH,LATENCY,MCV, label.

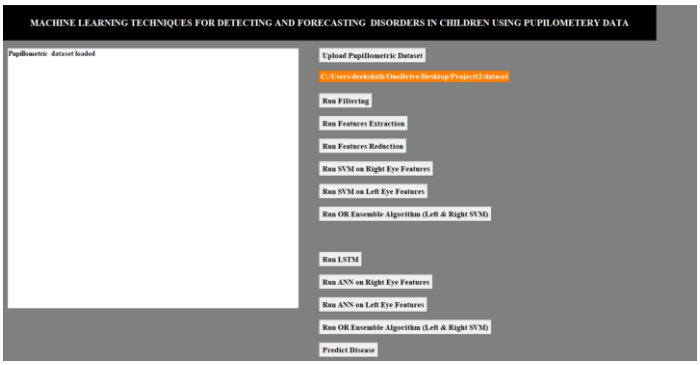

Figure-5 Data Set Uploading

In the figure 5 the path of the data set is shown to the user and also shows the number of patients data are avaliable in the dataset, in this case there are 593 patience data is avaliable.

Figure-6 Run Features Extraction

The figure 5 is about the features extraction process, where different features in the data set are extracted and are used for testing and training purpose the features in the data set are ID,MAX,MIN,DELTA,CH,LATENCY,MCV,label.

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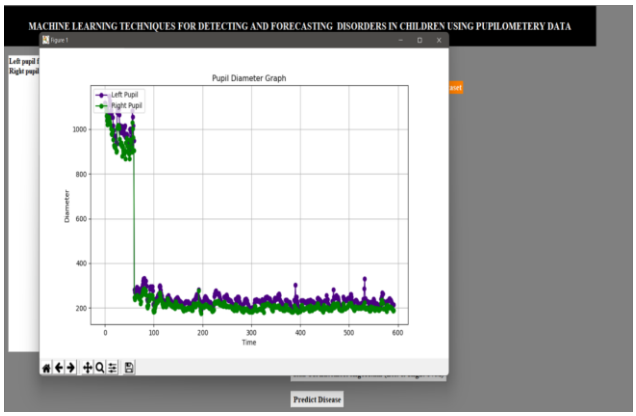

Figure-7

The figure 7 shows the pupil diameter graph which is between time and diameter of both left and right pupil.

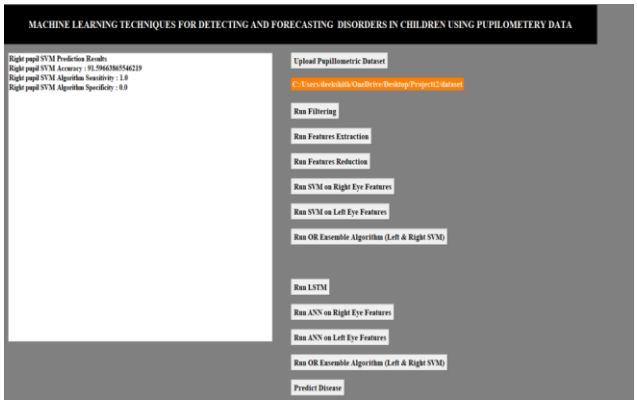

Figure-8

In the figure 8 SVM algorithm is performed on the right eye using the data set which was uploaded in the figure 6.2, Here the accuracy of the Support vector machine algorithm is shown.

Figure-9

In the figure 9 SVM algorithm is performed on the left eye using the data set which was uploaded in the figure 6.2, Here the accuracy of the Support vector machine algorithm is shown.

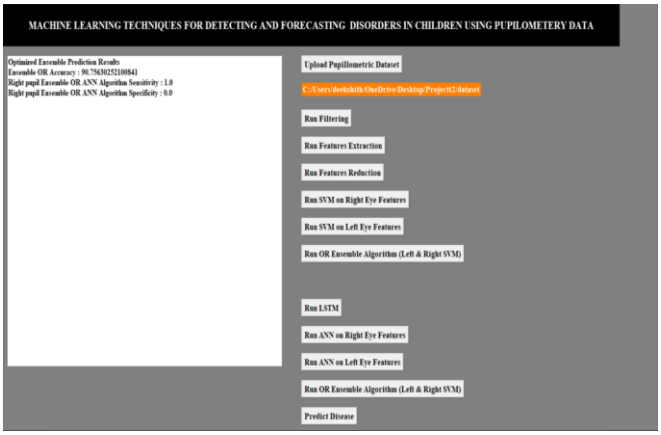

Figure-10

Figure 10 shows the OR ensemble algorithm is performed , where the or ensemble algorithm will combine both SVM right and left eye algorithms to get the final accurate answer for both eyes.

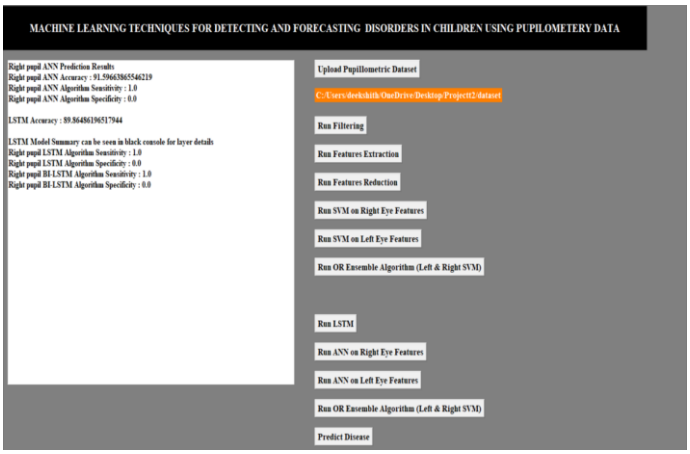

Figure-11

In the figure-11 Long short term memory algorithm is performed on the left and right eye using the data set which was uploaded , Here the accuracy of the LSTM is shown.

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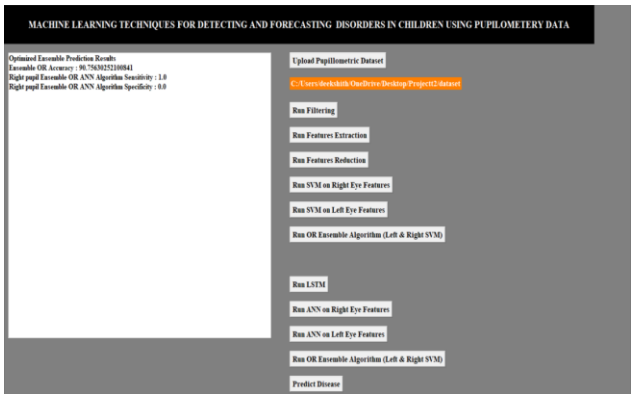

Figure-12

Here in the figure 12 the OR ensemble algorithm is performed , where the or ensemble algorithm will combine both ANN right and left eye algorithms to get the final accurate answer for both eyes.

V. CONCLUSION

This research presents a new method for assisting the clinical judgement to diagnose retinitis pigmentosa in juvenile patients based on a student reaction to chromatic light stimuli. The tool uses a machine learning technique based on an integrated model of two well configured SVMs to clean art objects, extract features, and aid with RP identification. In contrast to both left and right eyes, performance was tested using left-handed verification and was utilized to discover the optimal combination of SVM internal parameters. To improve the overall sensitivity of the CDSS, the class given to each eye was subsequently integrated with an OR-like mechanism; the integration system obtained 84.6 percent accuracy, 93.7 percent sensitivity, and 78.6 percent specificity. The minimal quantity of data accessible in this topic necessitates more research. Future plans involve experimenting with the same way on many devices. The persistent presence of movement objects emerged as a concern with a lot of evidence through- out the signal collection phase. This is dependent to the device's unique condition as well as the registered patients' minimum age. Devices with diverse frameworks, such as smartphone-based systems, will be studied. Furthermore, given the length of the adoption process, the method will let other programs get the interest of the younger patient (and his or her vision).

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