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A Study on Refractive Error in Patients of Chennai City in India during Covid 19 Pandemic Period

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Abstract

Objectives: To compare the results of techniques Decision Tree, Discriminant, KNN, SVM applied to pre Covid-19 data collected in 2018 and data collected during Covid-19 pandemic period (2020) patients in Chennai city. **Methods:** The variables in the data are Refractive Error in both left and right eye, Age, Gender, Educational Status, Employment Status, Nature of Job, Working Hours, Working with Computer, Watching TV, Sleeping Hours, Type of Food, Extra Activity, Light in Residence, Light in Work Place, Family Members Wearing Specs, Parents Wearing Specs, Other Disease and Other eye disease. **Findings:** In this study, 22 classification algorithms were applied to the data, and accuracy results as well as comparisons in two distinct sample sizes were obtained. Although adhering to the strict lockdown regulations helps to prevent the spread of COVID-19, it also negatively affects the visual health of those who are confined to their homes and have limited access to outdoor activities, leading to an excessive confidence on digital screens for studies or leisure. **Novelty:** Due to public health restrictions, the present Covid 19 pandemic has altered people's social lives all around the world. As a result, kids have spent more time in front of computer and television monitor screens, which is bad for their eyes. Refractive error affects a significant number of patients in Chennai. Across all kinds of refractive defects, myopia, hyperopia, astigmatism, and presbyopia constitute the most prevalent.

Keywords: Covid19; Refractive error; KNN; SVM; Decision Tree; Discriminant

1 Introduction

The capital of Indian state Tamil Nadu, is Chennai. Chennai is a Financial, ethnic, and intellectual center also the South India's commercial and industrial center. Chennai's 2019 population was estimated at 9,118,623 (9.1 million). Eyes are organs that recognizes light and transmits messages to the brain via the optic nerve. Eyes are a crucial sensory organ in humans that allows us to see. It enables vision and light perception, including the capacity to distinguish between distinct hues and varying levels of depth. Even though it is small, eyes are tremendously intricate biological structure. Eyes are roughly 0.9 inches tall, 1 inch wide, and 1 inch deep. The human eye has a 200-degree field of vision and can distinguish between 10 million different hues.

The eyes is a useful organ in our physique. Cerebrum of our brain processes raw visual data received from the oculus to grasp what is going in the surroundings one in contrast to learning about one's broad surroundings. What the eyes send to the cerebrum is translated by the cerebrum. We will not be capable to recognize writing, craftsmanship, or photography, and we will not be able to realize as much from little visual information. By analysing the illumination that things in the surroundings reflected or produce, our eyes enable us to recognize and explain the structures, colours, and proportions of those items. Eyes are capable to detect intense rays of light and glim rays of light, yet they are not able to detect an item at dark fundaments.

Refractive error is a common eye condition. When the eye is unable to focus clearly on an image of the outside world. Vision loss occurs as a result of refractive errors, which in some cases can be severe enough to cause visual impairment. Cycloplegia restrains the ability to accommodate intensity of eyes through obstructing activity of culinary muscle, permitting estimation of the eye's static or objective refractive error. Most ideal approach to acquire lack of motion of convenience to utilize Cycloplegic medications such as T+, CTC, HA+T, ROP, and T. Anticholinergic medications are usually cycloplegic because they prevent acetylcholine from acting in a muscarinic manner. The activity represses cycloplegia is caused by cholinergic stimulation of the ciliary muscle and iris sphincter. A remarkable ophthalmologic approach that can be used in addition to a comprehensive eye exam is tactile assessment. Six new visual muscles in the eyes will emerge under the supervision of tactile assessment [1,2].

To examine the corneal bend of the eyes, keratometry is used. A keratometer is a tool used to examine the cornea's flat and vertical arch. Keratometric testing is performed on kids whose eyes are tube-shaped. Children who score between 44 and 45 on the keratometric test have normal corneal shape, whereas those who score outside of this range are said to have odd corneal arches. An ophthalmologist can check for refractive errors as part of a comprehensive eye exam. An examination room in an eye doctor's office typically includes an exam chair, a phoropter, an eye chart, a slit lamp, and a stool for the eye care practitioner. You will probably spend the majority of your time looking through the phoropter, which is outfitted with various lenses, and deciding whether they're "good," "better," or "the same." The test is easy and painless. Your doctor will ask you to read the letter up close or from a distance. Then doctor will identify the error in eye, the mentions measuring refractive error on her OD&OS.

The following are the abbreviations used in the literature:

- Oculus Dexter abbreviated as OD, Latin for right eye from the patient's point of view. Oculus means eye.
- Oculus Sinister abbreviated as OS, Latin for left eye from the patient's point of view.
- OU is an abbreviated as Oculus Uterque, Latin for both eyes.
- SPH (Sphere): The number of lens power in dioptres required to correct near-sightedness (myopia) or far-sightedness (hypermetropia). Correction is equal in all meridians of eye.
- CYL (Cylinder): Degree of astigmatism. Cylindrical correction corrects the refractive error of astigmatism in the eye by cylindrically adding or subtracting refractive power at the meridian indicated by a given axis. If the number is followed by a minus sign (-), you have astigmatism. If the number is followed by a plus sign (+), you have hyperopic astigmatism.
- Axis: The lens meridian 90° from the meridian where the cylinder occurs. 90 degrees are subject to rule astigmatism, 180 degrees show astigmatism against the rules.

Key terms

These are the 4 frequent classes of refractive errors:

- Myopia (ShortSightedness)
- Hypermetropia (LongSightedness)
- Astigmatism
- Presbyopia

1. **Myopia:** The patient can readily see objects up close but struggles to notice stuff at a distance [3,4].
2. **Hyperopia:** The person is unable to clearly notice both nearby and distant items. In this situation, the retina is not in focus; rather, the rays of illumination being concentrated in back of the retina. Although hypermetropia can be found at any age, it typically shows up in older people.
3. **Astigmatism:** Precisely, Clearer vision requires a single point of focused light rays on the retina. However, astigmatism impairs vision because two or more foci of ray of light are focused on retina as a result of irregularities in the refracting surface.
4. **Presbyopia**: is the normal process of the eye's focus point maturing. Growing older results in the focus point's loss of flexibility, which makes it difficult to centre at close distances. After the age of 40, presbyopia typically becomes serious [5].

The life of children revolves around playing outdoor and indoor games, reading, and watching television, but covid 19 outbreak has left them with fewer options. The pandemic creates a significant challenge since children would be deprived of both appropriate and consistent physical exercises as well as the harmless and productive teaching space contact that is indispensable for their mental and physical health. India, like most other Asian countries, has seen an increase in the incidence and prevalence of myopia throughout time[6]. According to several research, increased screen usage, work from home and reduced outdoor activities are all key risk factors for refractive errors. Refractive errors are apparently more common in countries like China, where schools have replaced books with tablets and computers. Apart from the general consequences on the child's health, eye care practitioners should Remember that children might spend longer indoors all day but also participate in less outside activities, both of which are known risk factors for the start of refractive error. In the foreseeable future, children will occupy technically. The influence of technical gadgets extends, making it more necessary more important than before to increase awareness of the emerging adverse impacts of many such tactics mostly on evolving optical equipment[7].

By 2050, it is predicted that 50 percent of the world's population will have myopic refractive error[8]. If proper maintenance is not provided throughout the household incarcerations, the current system may hasten this prediction. In the realm of eye care, the term solitary confinement myopia is making its way into debates and arguments[9]. There are growing anxieties regarding boundaries on communal eye health programmes and travel limitations that limit access to seeking eye care. While a few studies have shown an augmenting prevalence of refractive error worldwide, there continues to be uncertainty about the magnitude of refractive error in Chennai after lockdown. Therefore, the current study used several methodologies to investigate the classification with respective refractive error in patients in Chennai during Covid-19 Pandemic Period[7,9].

2 Methodology

Information on 3042 individuals is gathered from the Chennai KK Eye Hospitals. during the month of march 2019 to October 2019 by the schedule method. Mens made up 50.09% of the participants at this private clinic while women made up 49.91%. All the info on 19 factors such as Refractive Error in both left and right eye, Age, Gender, Educational Status, Employment Status, Nature of Job, Working Hours, Working with Computer, Watching TV, Sleeping Hours, Type of Food, Extra Activity, Light in Residence, Light in Work Place, Family Members Wearing Specs, Parents Wearing Specs, Other Disease and Other eye disease.,[10,11] Refractive Error on both the left as well as the right eye are examined during this research's review. To evaluate the information, MATLAB model 17.0 is utilised. Employing frequency distribution (Figures 2, 3 and 4), the prevalence of refractive error in the participants' left and right eyes were examined. (https://docs.google.com/forms/d/e/1FAIpQLSfubFH3CLBIxihjtBAQziOmCOYWHj6p-vngwDNspW2Oxwr9CA/viewform?usp=sf_link)

Among the 230 respondents collected through online survey in Chennai, it could be seen that the gender is balanced with 44.4% males and 55.6% females. As reflected in the sample distribution (Table 1), the average age of respondents was 35.5 with 102 males and 128 females. Age structure of the respondents showed that largest population of study subjects were within the age group of 11 and 30 years, whereas minority of respondents were present in the age bracket of 41 and 60 years. Study subjects older than 51 years constituted 1.9% of males and none of the female respondents were older than 51 years. The data on 11 variables namely Age, Gender, City, Mobile usage timing per day, Working with Computer, Sleeping Hours, Extra Activity, Light in Residence, Having spectacles, Refractive Error both the left as well as the right eyes were examined in this research's review. Occurence of refractive error on the participants' eyes is analyzed using the frequency distribution Table 2[12].

According to studies by,[1] diagnosing eye diseases has grown to be a significant issue in contemporary medicine. Timely screening of eye conditions can stop consequences and loss of vision. The J48 decision tree seems to have the least mistake rates among the three implementations, and it also has the higher precision. Because sophisticated iterative parameter estimations are not necessary, Nave Bayes requires less computation time are indeed real-time-useable on a big dataset. SVMs can simulate intricate nonlinear decision boundaries, but their training times are incredibly slow.

The most important supervised learning method is the support vector machine (SVM), which additionally serves as the classification tool. In addition, SVMs are employed in a variety of different domains, including detection and recognition, text recognition, picture reprocessing grounded on fillings, biometric arrangements, and dialog detection. SVM is used to create a sole environment or a series of environments in immeasurable space or high length. This hyperplane can also be utilised to get a decent categorization. By doing so, one can create a hyperplane with the shortest distance to any class's nearest training point. A bigger margin is usually used to produce a reduced generalisation fault of the classifier. The support vector machine seeks out a environment that provides the exercise instance with the shortest distance. In SVM theories, it's also referred as margins. An ideal deviation is obtained for maximised hyperplanes. SVM has a number of other important qualities that help it get superior generalisation results. The main classifier in a SVM is a two-type classifier that turns data into a environment based on nonlinear or dimensionally higher data[13,14].

The decision tree (DT) classifier analyses the dataset's similarity and divides it into distinct courses. "Decision trees" are castoff to create data classifiers based on the feature selection, which doses and maximises the data division. Until the end conditions are met, these traits are divided into multiple branches. A decision tree is a various levelled tree an arrangement where every inside hub (non-leaf hub) addresses an assessment with a characteristic, each branch addresses a request result, and each leaf hub addresses a class name. The roots of a tree seems to be the node at its tallest position. Each tree has a single root, and there is only one path connecting any two hubs. A strong solution for predicting and identifying medical investigative concerns is a decision tree. Linear Discriminant Analysis (LDA) is a categorization and dimensionality reduction method which has 2 potential interpretations. First one is a probability observation; while the second one is a more methodical observation interpretation, is credited with Fisher. Understanding LDA's presumptions is made easier by employing the initial interpretation. The second explanation paints a fuller view of how dimensionality reduction is handled by LDA. Quadratic Discriminant Analysis (QDA) is a variant of LDA where the covariance matrices for every category of observations are calculated. Considering that we already understand that distinct classifications contain varying covariances, QDA is extremely advantageous. The disadvantage of QDA is that it cannot be used as a technique for dimensionality reduction. We have followed the mathematical formulations [15].

Various methods used are fine tree method high many leaves to distinguish among categories in a multitude of subtle ways (100 is the largest limit of divisions). Number of leaves on the medium tree approach for class differences that are more precise (20 is the largest limit of divisions). Fewer leaves are used in the coarse trees approach to create coarse class differences (the largest amount of splits is 4).

A generalisation of Fisher's linear discriminant, often used in statistical data but also Linear discriminant analysis, normal discriminant analysis, or discriminant function assessment are additional terms for identifying a linear mixture of features that separates among two or more groups of events or objects. A study using quadratic discriminants is used in generative models (QDA). As per QDA, each categories is assumed to possess a Gaussian distribution. The previous for the category will make up a part of the data points connected to the category. The average vector specific to that group is made up of the average of the input variables included within the group. Subspace Discriminant, interpretability is hard and the ensemble method is Subspace, with Discriminant learners. Flexibility of the model is medium — increases with Number of learners setting.

SVM or Support Vector Machine seems to be a linear model on incidents affecting both regression and classification. It works well for several real-world issues and therefore can handle both linear as well as non-linear tasks. A line or a hyperplane that summarize a given data set into groups is produced by the algorithms.

Quadratic SVM

This linear programme is an optimization technique where the functional form, inequity, as well as equality constraints are all linear. Nevertheless, the optimisation issue is known as a quadratic programme when the objective function is quadratic and all of the constraints were linear.

Cubic SVM

Emotion Detection but also Classifier Based Feature Extraction using Voice Signal. Among the most compelling and fascinating study regions of the world of ai technology is the identification of feelings via conversation.

Fine gaussian SVM

Increases by configuring the kernel scale. generates extremely precise class differences with the kernel scale set to sqrt(P)/4. Interpretability is challenging while modelling flexibility is average in moderate gaussian SVM. Medium differences, with the sqrt kernel scale (P). The model adaptability of coarse Gaussian SVMs is poor and their interpretability is difficult. with a kernel scale of sqrt(P)*4, where P is the number of predictors, produces coarse class differences [16,17].

The K-nearest neighbour approach is widely used in pattern recognition, machine learning, and other fields. The KNN method is a nonparametric method that can be used to solve classification and regression problems. The given input in both cases contains of the k-closest exercise examples in the component space. Regardless of whether we use KNN for relapse or characterization influences the result. The result of the KNN arrangement calculation is a class enrollment. Anything can be arranged by the larger part vote of its neighbors, with the article being given to the class that is generally pervasive among its K-closest neighbors (where K is a positive whole number, regularly little). With the number of neighbours set to one, a nearest neighbour classifier establishes finely defined distinctions across classes. KNN classifier is a well-liked biomedical classifications technology that uses the density estimation framework to detect the unfavourable results. The efficacy of the nearest neighbour criterion, as described in the references, forms the basis of the algorithms [17–20].

There are 6 different KNN Classifiers available, to categorise the information. Euclidean distance is used by the Fine, Medium, and Coarse KNN procedures to identify the closest neighbours.

Fine KNN is a nearest neighbour classifiers also with number of neighbours set to 1 and creates minute variations among categories. When the number of neighbours is adjusted to 10, the Medium KNN closest neighbour classification offers minimal differences besides a Fine KNN. A closest neighbour classifiers with a neighbour count of 100, coarse KNN creates coarse distinctions across categories. The nearest neighbour classifiers which makes usage of the cosine distance metric is called cosine KNN. The cubic distance metric is used by the nearest neighbour classifiers known as cubic KNN. A nearest neighbour classification which makes advantage of distance weighting is weighted KNN[15,19–21].

Boosted Trees, interpretability is hard and the ensemble method is AdaBoost, with Decision Tree learners. Flexibility of the model is medium to high — increases with number of learners or maximum number of splits setting. Bagged Trees, interpretability is hard and the ensemble method is Random Forest Bag, with Decision Tree learners. Flexibility of the model is high — increases with Number of learners setting. RUS Boost Trees, interpretability is hard and the ensemble method is RUS Boost, with Decision Tree learners. Flexibility of the model is medium — rises with settings for the largest amount of splits or learners. beneficial for skewed statistics (with many more observations of 1 class).

A classification model uses a confusion matrix. This means that the response values are categorical. In order to assess the anticipated response value towards the real reaction values for every observations in the testing set, the model suggests a response value for every observation in the testing set. Therefore, the confusion matrix evaluates how accurate the developed predictive algorithm is. Mostly in cases where the genuine answer values are computed are confusion matrices helpful during evaluating the model. However, once up and running, it's impossible to know the observation that he is TP/TN/FP/FN unless you have a system that checks the actual response values. The purpose of the confusion matrix is to provide expected values such as sensitivity/specificity, but there is no guarantee that these values will be met in production[22,23].

Confusion Matrix

		Predicted Class	
		No	Yes
Observed Class	No	True Negative	False Positive
	Yes	False Negative	True Positive

Fig 1. Confusion matrix

Accuracy measures overall accuracy of the model classification.

Accuracy = (TP+TN)/(TP+FP+TN+FN)

Precision: TP / (TP + FP) The percentage of positive predictions those are correct.

Recall: TP / (TP + FN) The percentage of positive labeled instances that were predicted as positive.

F1-Score: 2(PR)/(P+R) Combined measure that assesses precision/recall tradeoff.

The refractive error false positive rates as compared to true positive rate is shown graphically by the ROC curve. The true positive and false positive rate-based vertical graph serves as a flawless representation of the ROC curve. Greater perfectness increases the precision. It is often used to figure out the classifier's numerous different properties, such particularity and sensitivity. The testing seems to be more reliable the nearer the curve is to the top and left borders of the ROC space.

3 Results and Discussion

One of the most important elements of population composition is the age-sex structure. Almost all population traits change dramatically as people get older. Because the majority of population analysis is based on the population's age-sex structure, age statistics are crucial. India has one of the world's highest proportions of people in the younger age categories[9].

Figure 5 shows the pie charts of respondents in Chennai City during covid 19 pandemic period. It could be seen that 91 % of the respondents opted homely food while only 9% of people depended on outside food during Covid 19 pandemic period.

Coding	Educational Status (%)	Employment status (%)	Nature of job (%)	Working hrs (%)	Working with computer (%)	Spend in TV (%)	Sleeping hrs (%)	Type of food (%)	Extra Activity (%)
1	144 (4.7)	1422 (46.7)	396 (13.0)	318 (10.4)	2010 (66.1)	534 (17.5)	48 (1.5)	2484 (81.7)	426 (14.0)
2	612 (20.1)	1620 (53.3)	2040 (67.1)	342 (11.2)	558 (19.3)	552 (18.1)	510 (16.7)	96 (3.1)	228 (7.5)
3	738 (24.2)		606 (19.9)	744 (24.4)	162 (5.3)	846 (27.8)	1608 (52.8)	462 (15.2)	834 (27.4)
4	258 (8.4)			1242 (40.8)	156 (5.1)	732 (24.0)	822 (27.0)		1554 (51.1)
5	690 (22.6)			396 (13.0)	156 (5.1)	312 (10.2)	54 (1.7)		
6	390 (12.8)					54 (1.7)			
7	186 (6.1)					12 (0.3)			
8	24 (0.7)								

Fig 2. Frequency Table

Coding	Light in residence (%)	Light in Work Place (%)	Wearing specs in family members (%)	Wearing specs in Parents (%)	Other disease (%)	Other eye disease (%)	Right eye (%)	Left Eye (%)	Gender (%)
1	18 (0.5)	66 (2.2)	1278	1278 (42.0)	1806 (59.4)	1788 (58.8)	324 (10.6)	498 (16.4)	1524 (50.0)
2	1860 (61.1)	1884 (61.9)	1020	1020 (33.5)	546 (17.9)	6 (0.2)	12 (0.4)	24 (0.8)	1518 (49.9)
3	222 (7.3)	240 (7.9)	408	408 (13.4)	216 (7.1)	396 (13.0)	0	0	
4	936 (30.7)	852 (28.0)	240	240 (7.9)	474 (15.6)	354 (11.6)	258 (8.5)	6901 (22.7)	
5	6 (0.2)		78	78 (2.6)		378 (12.4)	12 (0.4)	12 (0.4)	
6			18	18 (0.6)		120 (3.9)	0	0	
7							912 (29.9)	504 (16.6)	
8							108 (3.6)	84 (2.7)	
9							18 (0.6)	30 (0.9)	
10							912 (29.9)	720 (23.7)	
11							6 (0.2)	6 (0.2)	
12							6 (0.2)	6 (0.2)	
13							474 (15.6)	468 (15.4)	

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7							912 (29.9)	504 (16.6)	
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10							912 (29.9)	720 (23.7)	
11							6 (0.2)	6 (0.2)	
12							6 (0.2)	6 (0.2)	
13							474 (15.6)	468 (15.4)	

Fig 4. Frequency Table

Table 1. Demographic profile of respondents regarding Gender and Age

Age	Male = 1	Female = 2
11-20	42	72
21-30	44	48
31-40	12	6
41-50	2	2
51-60	2	0
Sum	102	128
Mean	20.4	25.6
SD	21.04281	32.6006135

54% of surveyed people had better sleep time (6 to 8 hours) while a few of the respondents (9%) had the lowest sleep time of below 4 hours. As per the results of survey, about 28% of respondents wore spectacles while majority (72%) of respondents did not use spectacles. Among the 230 respondents, 34% of the people spend 4 to 6 hours with mobile every day and 21% of study subjects use mobile for 6 to8 hours. 11% of study subjects use computers for more than 6 hours and majority (63%) use computers for 1 to 2 hours. The present study also reveals that, 12% of respondents did yoga, 18% did exercise, 19% participated in sports activities during covid 19 pandemic, whereas majority of the respondents (51%) were engaged in other extracurricular activities. Majority of the respondents (64%) were found to use tube light at their homes while 29% of people used LED light, 8% used CFL and minority (1%) used filament bulb. The refractive error measurements for 230 respondents were 13 (N=167), 10 (N=11), 9 (N=2), 7 (N=20), 4 (N=18), and 1 (N=12) respectively in case of left eye whereas 13 (N=166), 10 (N=18), 8 (N=2), 7 (N=40), and 1(N=4) respectively in case of right eye, which is showing 72% of people had normal right eye while 73% of respondents had normal left eye[5,6,8].

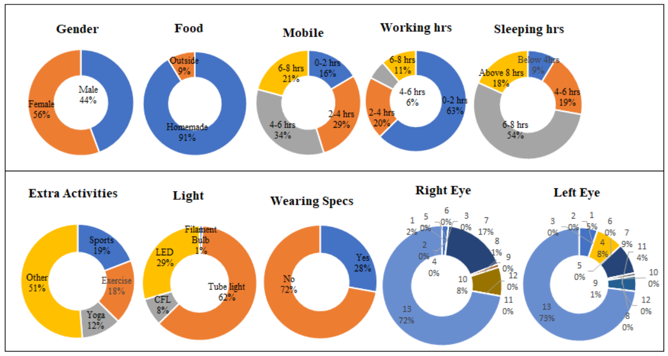

Fig 5. Pie Charts of respondents in Chennai City during covid 19 pandemic period

Table 2 shows the Classification accuracy of all the study classifiers. The study results showed that, highest accuracy of 100% was reached by using Bagged tree, Weighted KNN, and Fine KNN in case of Right Eye (RE). Cubic SVM, and subspace KNN had next highest accuracy of (99.1%) in case of RE. In case of Left Eye (LE), highest accuracy (99.1%) was reached by Cubic SVM, The next highest accuracy (98.7%) was reached by Fine KNN, Weighted KNN, Boosted tree, and Bagged tree in case of LE.

The Table 2 shows the Classification accuracy of various methods for RE and LE. The resultant accuracy values show that the overall accuracy is higher for RE than for LE. The Linear Discriminant and Quadratic Discriminant prediction models showed no results and since both the methods are not suitable for our research data. Fine KNN and Weighted KNN give the largest accuracy for both the RE and the LE. The Coarse KNN and Boosted Tree models give the lowest accuracy of 72.2% for the RE. The Coarse KNN give the lowest accuracy (73%) and for the LE.

Table 2. Predictive accuracy of all the classifiers (pre covid data - 2019)

N=3042 Response Variable – Left & Right Eye (Accuracy in LE & RE) Predictors: 17 Variables		
Methods	**Accuracy in RE**	**Accuracy in LE**
Fine Tree	61.8%	65.9%
Medium Tree	46.2%	47.0%
Coarse Tree	39.3%	38.4%
Linear Discriminant	36.1%	37.4%
Quadratic Discriminant	No result	No result
Linear SVM	37.9%	42.7%
Quadratic SVM	85.2%	91.2%
Cubic SVM	99.4%	99.6%
Fine Gaussian SVM	100.0%	100.0%
Medium Gaussian SVM	89.9%	92.5%
Coarse Gaussian SVM	35.9%	41.7%
Fine KNN	100%	100%
Medium KNN	50.10%	52.30%
Coarse KNN	36.70%	38.10%
Cosine KNN	48.80%	52.50%
Cubic KNN	50.70%	53.10%
Weighted KNN	100%	100%
Boosted Tree	49.2%	51.6%
Bagged Tree	100.0%	100.0%
Subspace Discriminant	34.8%	38.8%
Subspace KNN	99.9%	99.9%
RUSBoosted Trees	24.2%	31.3%

Before covid study results showed that, highest accuracy of 100% was reached in case of Bagged tree, Weighted KNN, and Fine KNN in case of right eye. Cubic SVM, and subspace KNN had similar results when compared with the highest accuracy predictors. In case of left eye. Cubic SVM, Weighted KNN, Boosted tree, and Bagged tree showed approximately similar results when compared with the highest accuracy predictors

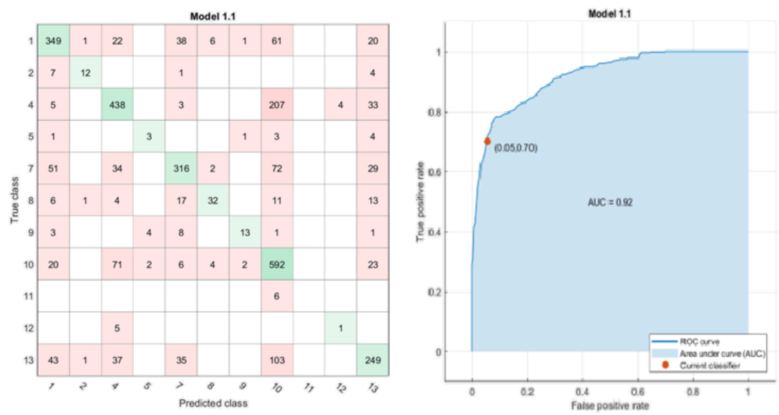

Fig 6. Confusion Matrix and ROC Curve for Fine Tree in Left Eye

It has a good possibility that perhaps the classifiers would be capable of distinguishing the positive class results out from negative class values using a confusion matrix and ROC curve for fine tree in the eye. This also applies to all 22 classifier techniques.

Table 3. Performance metrics for classifier in Refractive error

Class	n (truth)	n (classified)	Accuracy	Precision	Recall	F1 Score
1	485	498	90.63%	0.7	0.72	0.71
2	15	24	99.51%	0.5	0.8	0.62
4	611	690	86.03%	0.63	0.72	0.67
5	9	12	99.51%	0.25	0.33	0.29
7	424	504	90.27%	0.63	0.75	0.68
8	44	84	97.90%	0.38	0.73	0.5
9	17	30	99.31%	0.43	0.76	0.55
10	1056	720	80.54%	0.82	0.56	0.67
11	0	6	99.80%	0	0	0
12	5	6	99.70%	0.17	0.2	0.18
13	376	468	88.63%	0.53	0.66	0.59

The performance metrics Precision, Recall, and F-Score are important in assessing the classifier together with high precision. Table 3 lists the measurements that were acquired for the SER system that was demonstrated.

Correctly classified values: 349+12+438+3+316+32+13+592+0+1+249 = 2005

Total number of values: 3042

Overall accuracy: 2005 / 3042 = 0.6591 or 65.91% (Fine Tree) , Similarly we calculate all the classifier methods.

The covid study results showed that, highest accuracy of 100% was reached in case of Bagged tree, Weighted KNN, and Fine KNN in case of right eye. Cubic SVM, and subspace KNN had similar results when compared with the highest accuracy predictors. In case of left eye. Cubic SVM, Weighted KNN, Boosted tree, and Bagged tree showed approximately similar results when compared with the highest accuracy predictors

Table 4. Predictive accuracy of all the classifiers (Covid-19data - 2020)

N=230, Response Variable – Left &Right Eye (Accuracy in LE & RE) Predictors: 9 Variables		
Methods	**Accuracy in RE**	**Accuracy in LE**
Fine Tree	94.3%	86.5%
Medium Tree	94.3%	86.5%
Coarse Tree	91.7%	81.3%
Linear Discriminant	No result	83.9%
Quadratic Discriminant	No result	No result
Linear SVM	89.1%	83.0%
Quadratic SVM	96.5%	94.3%
Cubic SVM	99.1%	99.1%
Fine Gaussian SVM	96.5%	97.8%
Medium Gaussian SVM	93.9%	88.7%
Coarse Gaussian SVM	89.6%	82.2%
Fine KNN	100.0%	98.7%
Medium KNN	84.8%	76.5%
Coarse KNN	72.2%	73.0%
Cosine KNN	87.0%	77.4%
Cubic KNN	82.2%	77.8%
Weighted KNN	100.0%	98.7%
Boosted Tree	72.2%	98.7%
Bagged Tree	100.0%	98.7%
Subspace Discriminant	73.5%	77.4%
Subspace KNN	99.1%	97.8%
RUSBoosted Trees	76.1%	75.7%

4 Conclusion

Over the last two decades, digital technologies have advanced dramatically. This it resulted to more people are utilizing electrical gadgets by people of all ages. Children are the most vulnerable members of the population, as they develop ocular abnormalities at a young age as a result of extended use of electronic gadgets. One of the most prevalent eye abnormalities in children is refractive error. There are a number of variables that lead to eyesight loss. The key elements that induce refractive errors can be discovered using machine learning algorithms. Algorithms for machine learning have the potential to classify those who are at risk for Refractive error. The optimum models for the Right Eye data set (Fine KNN, Weighted KNN, Bagged Tree) were obtained by comparing 22 supervised machine learning approaches such as logistic regression, decision tree, support vector machine, and K-nearest neighbour. In Decision Tree and SVM, the data is partitioned to discover accurate results, whereas in KNN, the data is used to locate similar values. Each algorithm does have a distinctive blend of benefits and drawbacks, and no algorithm has ever met all of the criteria and requirements. Because each algorithm has its unique set of requirements, algorithms should be chosen in accordance with them.

Therefore, it can be concluded from the present study, Fine KNN, and Cubic algorithm showed maximum 100% and 99.1% accuracy respectively and both easier and more accurate than the decision tree and discriminant analysis.

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