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A Machine Learning Approach for Estimating Visual Acuity Using the Gradient Descent Algorithm

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Abstract— About 2.3 billion people worldwide suffer from eye defects, and many do not have access to effective eye diagnosis. The conventional diagnosis of the eye involves measuring the Visual Acuity (VA) using a chart. Researchers have attempted to achieve greater accuracy in VA estimation by developing software systems. However, many software systems have not reasonably improved the diagnosis procedure. This research provides a better approach to estimating VA using machine learning, resulting in a more accurate diagnosis. An Optimized Eye Diagnosis System (OEDS) was developed as a framework for building VA estimating software systems for eye diagnosis. The result is an improved method of estimating VA shown by various plots of the cost function. We have discussed strategies for using a linear regression function to model factors that affect an estimate in medical diagnosis. The theoretical framework developed bridges the gap between the optometrist and a software developer that seeks to build a corrective lens recommendation system based on Artificial Intelligence (AI). We have shown how the accuracy of the VA depends on a number of demographic factors and the detailed procedure for correctly implementing the algorithm on any programming platform illustrated in this work using the Matlab programming language.

Keywords— Machine Learning; Visual Acuity; Gradient Descent; Cost function; Diagnosis

I. INTRODUCTION

Machine Learning (ML) is still an emerging area of computer science that has gained credence among numerical scientists, statisticians, and researchers [1, 2]. It has proven propitious in theory and practice and has provided tools for problem-solving in social science, physical science, and humanities. According to [3], we are in a new era of computing where problems that hereto seemed impossible are modeled and solved with travail effort. Hence, the role of thinking machines is now an indispensable part of human life [4].

The concepts of ML have been used to solve many prediction problems in several areas [2]. ML methodologies are employed in learning, military, cyberspace, radiology, genomics, parallel computing, graphic processing, agriculture, and other fields [5, 6]. In medicine, earlier approaches used expert systems that make inferences from a knowledge base using algorithms that have if.. then… else.. structures [7, 8]. Diagnosis is recently conducted using smarter Machine Learning methods to model patterns from data to make reasonable inferences for disease detection and control [7]. This novel paradigm is gaining popularity among medical practitioners, including optometrists, ophthalmologists, medical technicians, and other health workers.

Machine Learning attempts to mimic human reasoning and interpretation of events. However, human learning is slow; consider the time it takes for a person to develop professionalism in any field of specialization. However, computers can learn within a few seconds, depending on the 'smartness' of the training algorithm [9]. There are several approaches to this. Popular methods include supervised, unsupervised, and reinforcement learning [10]. The supervised learning approach is suitable where the machine is trained to make inferences given several sample data. [11] used a supervised learning algorithm to find the best volatility targeting model on a fixed-income instrument and mentioned that the selection of features of the training data is essential in the learning process. His work showed how efficient supervised learning algorithms could fit in regression problems. The Gradient Descent algorithm is an example of a supervised learning algorithm.

Accuracy and precision are significant concerns in medical diagnosis because errors in medical procedures can lead to severe complications and, worst case, death. Furthermore, medical practitioners are adamant about adopting software without understanding the decision rationale behind such applications [12]. Hence, the need to train and retrain medical practitioners to accurately carry out the process [13], using computer-aided technologies [14]. [9, 12], showed that the computer system has helped achieve a more accurate diagnosis procedure.

Visual Acuity (VA) refers to a person's ability to see and identify objects [15]. The World Health Organization (WHO) defined Visual Acuity (VA) to be the vision level of an individual, which consequently means their "ability to see details clearly regardless of the distance of the object" [16]. Several kinds of problems affect the eye, such as glaucoma, cataract, conjunctiva, corneal disorder, and other refractive error [16, 17, 18]. During eye diagnosis, the VA of a patient is measured to determine corrective recommendations, especially in the case of refractive eye defects, which are mostly corrected using lenses. The VA is measured separately for the left and the right eye [16]. According to [13, 15], the clarity of vision depends on the distance between the retina and the brain. Therefore, changes in the lens due to disease or aging significantly cause vision impairment.

In the diagnosis process, VA estimation is influenced by several factors that are subject to change [19]. The advantage of using machine learning in estimating VA is that once the machine has been trained, it can provide a more accurate estimate for every new case [3, 4, 20]. ML makes a machine smart enough to carry out a new task in a domain without having to be explicitly programmed [4]. This is captured in Tom Mitchell's famous definition thus: A computer program is said to learn from an Experiment (E) with respect to task (T) and some Performance measure (P) if its performance on T measured by P improves with experience E [21]. The necessity of such learning machines is amplified in situations where it is not optimal to explicitly write programs, considering the high cost of running programs in terms of system resource usage and time complexity [21].

In 2019, the WHO reported that 2.2 billion people have vision impairment [16]. An earlier report by [22] showed 1.1 billion cases in 2017. Apparently, the number has exceeded the projected 1.7 billion by 2050 estimate of the Vision Loss Expert Group (VLEG) [23] , and cases do not seem to be declining (figure 1).

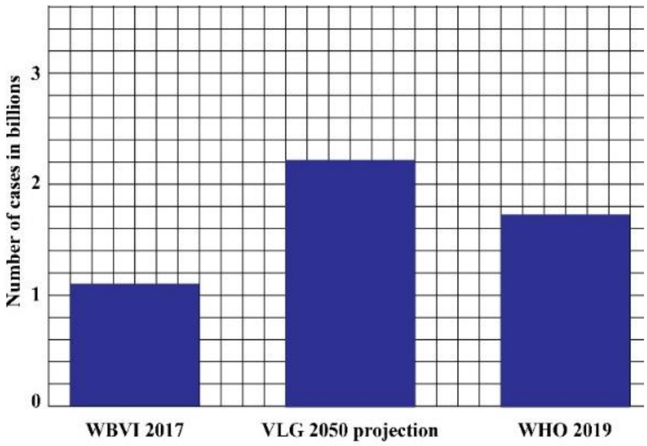

Figure 1. Reported cases of blindness by various interest groups

The causes of eye defects vary and may include heredity, aging, disease e.t.c During the treatment, the VA is measured by comparing the patient's reading to the normal eyesight, generally 20/20 [15]. The numerator indicates the distance (in meters or feet) of the patient being diagnosed, while the value at the bottom indicates the distance from which a person with good eyesight can read the chart. When VA is inaccurately measured, the optometrist might administer the wrong treatment, causing serious complications [13]. In work carried out by Oye to develop an Expert system that measures the VA and prescribes the right correctional lens, the researcher pointed out that an error in the reading might cause the system to recommend the wrong lens. Even though studies have shown that wearing the wrong eye lens does not further impact the eye, it can have unpleasant side defects [15, 24, 25].

No vision screening test is known to have attained a 100% rating in terms of sensitivity, specificity, and Positive Predictive Value (PPV) [26]. The problem with using the Snellen board to estimate the VA is that there are high chances of error due to inaccurate estimation. Many factors influencing the process are subject to epidemiological transition [19, 23]. Consider where the light intensity of the diagnosis environment might be insufficient; using the Snellen chart or the tumbling E board might fail to yield an accurate result. Figure 5.3 visually elucidates how the VA is related to the illumination of the measuring instrument. Some patients suffering from Eugleuma who have only partial vision may not be able to read letters on the chart [27]. Also, the approach might fail for patients who can sense the presence of light but may find it difficult to read from the board since it only measures a VA of 1/60 and above. The Snellen board measurement requires keen examination, and a lack of detailed examination might result in errors [28]. In cases where the VA is lower than the 1/60 value, the patient cannot detect the inscription on the board, and other means of measurement have to be used [15, 27]. Moreover, the boards are scripted with letters or symbols that are weighted by definite values. The weighting makes it challenging to assign an approximate value when the eye vision falls between two letters on the same scale level.

According to the WHO, a 3/60 VA reading is the blindness boundary value for eyesight, assumed to be the international standard of comparison. Measures below this level are considered blindness. However, certain factors determine the VA of a person tested under certain conditions. Some national health organizations disputed that the conventional estimation method is not relative and cannot be used to generalize the blindness level. For example, the definition under the National Programme for Control of Blindness (NPCB), the Government of India states otherwise [29]. The argument stems from the fact that factors such as age, light intensity, contrast, pupil size, and temperature also reasonably impact the estimate. Consider where the luminosity of the environment where the diagnosis is conducted might increase or decrease the VA level. A patient whose VA was estimated to be slightly below the blindness level might have a higher VA with increased light Intensity. Considering the patient's age range being diagnosed, [27] reported that it is challenging to use the Snellen board to take the VA reading of young children. In setting a global standard for blindness, it might be argued that older patients above 60 should not be weighed on the same scale as younger patients below 30 years of age. In fact, the definition and groupings of vision are continuality being modified; hence it is challenging to set an international standard or generalization [30].

As posed by [19, 22], it is, in general, difficult to use charts to measure the VA for patients with particular cases and generalize the result to answer questions like:

- What is the general blindness level? And how do we determine this among several age groups?
- How does each causal factor affect eyesight?
- How does the VA change over time, and what is the best-recommended treatment?

Unless the diagnostic procedure addresses the questions above are addressed, there is no way to set standards for software systems that are designed to assist the optometrist in reading a patient's VA. Yet, out-patients need to easily monitor the responses of their eye to treatment without visiting the eye center each time. This research work provides a standard machine learning framework on which mobile, internet-based, and microcontroller programs can be built and achieve the optimum accuracy in estimating the VA.

It is important to note that there is no way to combine reading for the left and right eye; professionals in the medical field suggest having both eyes open rather than closing one eye while the diagnosis takes place and other methods [3031]. However, the model developed could be extended to accept both eyes' reading input and produce an overall reading. It is a promising system to research a better method of estimating the VA to complement the use of manual boards. The OEDS developed in this research produced a better estimate of the VA when fed with the factors stated above.

It is time-saving to use AI systems along with expertise in case of emergencies. The number of medical practitioners in most countries is inadequate to satisfy the demand for eye care [31]. There are usually limited resources available; in most cases, the diagnosis is assiduous and time-consuming [26]. In Ophthalmology, the method of diagnosing eye defects involves using a board to estimate a patient's VA. [1] states that the optometrist conducting the experiment observes a patient that stands at a measurable distance of 20 meters [3] from the board. For an individual to understand an object on sight, the visual faculty must be able to differentiate between the two endpoints of the symbol at a distance that satisfies the 5 minutes of the Arc principle shown in figure 6.

Other factors which cannot be overlooked in the estimate of VA include weather conditions, humidity, and demographic factors [14]. Further complicating the estimation process is the fact that these factors vary at different times of the day [15]. Patients trying to guess the letters by recalling earlier readings also affect the current reading of VA [15]. Hence, the estimate of VA is better modeled as a machine learning problem as it provides a more dynamic and accurate measurement for each question.

Section I of this paper has laid the foundation of this work by explaining the need for an ML-based system of eye diagnosis. In section II, we discussed several works in areas where the proposed approach has proven to be prolific. Section III discussed the mathematical and theoretical concepts used. We showed how to appropriately apply the framework developed and evaluated the result obtained using the framework in section IV. Areas that require further research and other possible applications of the framework were discussed in section V.

II. Related Work

Researchers have proposed several approaches to handle the challenges associated with the measurement of VA during eye diagnosis. [27] Proposed a 'differential visual acuity' estimation. The approach used was to compare a patient's VA in a crowded and uncrowded setting. However, the result of the estimate does not indicate a tangible improvement compared to the standardized board testing in a normal setting. The researcher suggested a simpler different acuity test for younger children, but it is not pragmatic to develop a separate system for every distinct case. Another approach by [25] employs the backward chaining algorithm to infer the VA from a knowledge-based system. Even though the system used a computerized testing board, no optimization algorithm enabled the Expert system to make accurate inferences. Furthermore, the system developed is slow and requires a new dataset for every new variable introduced. Successful eye diagnosis methods developed over the year involve some form of machine learning system to assist the Ophthalmologist.

Several healthcare techniques have been revolutionized by machine learning. [32] developed models for diagnosing cancer using regression models. Sample datasets from cancer cells were used to train the machine, which predicts the malignancy of the disease with nearly 95% accuracy. The researchers opined that machine learning enables the computer to achieve a high degree of accuracy in disease prediction. Also, the complex task can be performed with trivial effort through ML approaches. In medicine, the machine is trained to relate medical features to an outcome, an application of supervised learning. An example of an efficient supervised learning algorithm is gradient descent. Different ML algorithms perform differently depending on the nature of the problem. Experimental approaches are used to select the best ML approach to use in each case [9].

When formulating a supervised learning model, finding relevant parameters to the scenario is paramount rather than just trying to fit the model from a statistical point of view [33]. As described by [14], data can contain hidden features that computers can pick up and appropriate to produce relevant results. For example, the Heart Disease Prediction System (HDPS) uses neural networks leveraging the sampled data's factors such as cholesterol levels, blood pressure, and gender. Other features that were fed into the HDPS, like obesity and smoking, resulted in a more accurate prediction. A form of GD known as Backward propagation was used as the prediction algorithm.

The Gradient Descent approach has been applied to solve several problems in medicine. [31] designed a system for predicting cardiovascular disorders powered by the GD optimization algorithm. The method used was to feed datasets like the type of chest pain, gender, and age through several layers of the machine. Then the system reasons to figure out a weight for each variable and update the weight at every iteration through backward propagation. The GD-enhanced system was better in terms of sensitivity and accuracy compared to other machine learning such as Naïve Bayes and Artificial Neural Networks. The GD-supervised learning algorithm is based on Newton's idea of finding the root of a function [34]. It is a robust graphical model hence, provides a condensed way to represent variable dependencies [33].

The application of other Artificial intelligence methods for real-life medical diagnosis poses a number of challenges. [35] used a Deep Neural Networks (DNN) approach to obtain changing blood pressure. It uses the standard deviation function with the root mean square error to estimate the model's accuracy. While the algorithm successfully predicts the blood pressure with minimal mean error, a large amount of dataset is required for optimal performance of the deep neural network model; otherwise, the machine would find it difficult to understand the problem [36]. An advantage of GD over other AI algorithms, such as the DNN, is that the GD does not require a large amount of data to optimize the problem. [11] pointed out that the GD approach is sensitive to features that vary according to the problem domain.

Due to the increasing demand for eye healthcare, there is a need to strengthen eye diagnosis, make the procedure easily manageable, and make the result more reliable [19, 26]. The OEDS developed in this research can be implemented as a system to improve the accuracy and reliability of eye diagnosis. The supervised learning method used ensures that the predicted estimate is the best fit given a number of output data (Y) from the sample space. The cost function tells the difference between the real value of Y and the output value from our hypothesis h(x).

III. METHODOLOGY

The procedure followed in formulating the system is to design a hypothesis function. We visualized the data and proposed a linear regression function to fit values for the thetas. Next, we used a cost function to estimate how good the algorithm is and used the gradient descent to iteratively improve the hypothesis using a design matrix to harness the vectorization capability of the Matlab programming environment. Finally, the EODS was trained using sample data from a publically accessible medical database at health data repository online so that the algorithm is easily used to estimate VA for new cases that were not part of the training data samples.

A. MATHEMATICAL MODEL OF THE PROBLEM

Given a number of data samples, as shown in Table 1.1 below, the problem was modeled as a quadratic polynomial suitable for computation. The output variable or the dependent (Y) is a function of a number of features labeled x, each representing a factor that influences the measurement. For a sampled VA indexed *i* ranging ` to m (number of features), given a set of influencing factors *x*, we have the function h(x) as follows:

$$\boldsymbol{h_\theta(x) = \theta_0 + \theta_1 x_1^i} \quad (1$$

θ is the coefficient of factor x.

For a multivariate problem with multiple features, the function is rewritten:

$$\boldsymbol{h_\theta(x) = \theta_0 x_0 + \theta_1 x_1 + \theta_2 x_2 + \cdots + \theta_n x_n} \quad (2$$

The estimation of VA is suitable as a machine learning problem due to the unstable nature of factors that influence the process [3] and the ability to model it as a computable problem. It is vital to iterate that proper feature selection and scaling ensure that the program does not run into the problem of under-fitting or over-fitting, as supervised learning is very sensitive to features [11], [23].

B. THE COST FUNCTION

The cost function G(θ) of the model is a mean of the sum of the squared function taken as the difference between the prediction of the model and the actual values (also called the squared error cost function). Let G(θ) be the cost function for equation (2) as follows:

$$\boldsymbol{G(\theta) = \frac{1}{2m} \sum_{1=1}^{m} (h_\theta(x^i - y^i))} \quad (3$$

G: is the summation of all mean of squared difference

i: represents a training sample

m: is the total number of the training samples

The job of the cost function above is to return the difference between the actual dataset and our prediction function h.

C. THE OPTIMIZATION FUNCTION

The goal of optimization is to minimize or maximize the cost function. To ensure that the model above produces a feasible solution in the solution domain, define an objective function for the problem as follows:

$$\underset{\boldsymbol{\theta}}{\boldsymbol{minimize}}\, \boldsymbol{G}(\boldsymbol{\theta}) = \frac{1}{2m}\sum_{1=1}^{m}(\boldsymbol{h}_{\boldsymbol{\theta}}(\boldsymbol{x}^{i} - \boldsymbol{y}^{i}))^{2} \qquad \textbf{(4}$$

The Gradient descent function is based on the iterative function equation (4), which shows how to estimate the best values for θ so that the cost G is minimized. It iteratively assigns values for θ so that the G(θ) outputs are the least cost.

Say forθ_0,θ_1, repeat until converge {

$$\boldsymbol{\theta}_{g} := \boldsymbol{\theta}_{g} - \boldsymbol{\alpha}\frac{\partial}{\partial\boldsymbol{\theta}}\boldsymbol{G}(\boldsymbol{\theta}_0, \boldsymbol{\theta}_1) \qquad \textbf{(5}$$

}

$\frac{\partial}{\partial\theta}$ represents the partial derivative of the cost function G with represent to the theta values

α is known as the learning rate, which defines the steps taken by the algorithm to arrive at the global minimum

From equation (4), substituting G into equation (5) yields

$$\frac{\boldsymbol{\partial}}{\boldsymbol{\partial\theta_g}}\frac{\mathbf{1}}{\mathbf{2m}}\sum_{\mathbf{1=1}}^{\boldsymbol{m}}(\boldsymbol{h}_{\boldsymbol{\theta}}(\boldsymbol{x}^{i} - \boldsymbol{y}^{i}))^{2}$$

But equation (1) defines the function h so that the final partial derivative becomes

$$\boldsymbol{\theta}_0 := \boldsymbol{\theta}_0 - \boldsymbol{\alpha}\frac{1}{2m}\sum_{1=1}^{m}(\boldsymbol{h}_{\boldsymbol{\theta}}(\boldsymbol{x}^{i}) - \boldsymbol{y}^{i}), \text{ for theta 0}$$

, and

$$\boldsymbol{\theta}_1 := \boldsymbol{\theta}_0 - \boldsymbol{\alpha}\frac{1}{2m}\sum_{1=1}^{m}(\boldsymbol{h}_{\boldsymbol{\theta}}(\boldsymbol{x}^{i}) - \boldsymbol{y}^{i})\boldsymbol{x}^{i}, \text{ for theta 1.}$$

Generally, we define an iterative model of the gradient descents in a multivariate problem domain as follows:

Repeat until convergence {

$$\boldsymbol{\theta}_{g} := \boldsymbol{\theta}_{g} - \boldsymbol{\alpha}\frac{1}{2m}\sum_{1=1}^{m}(\boldsymbol{h}_{\boldsymbol{\theta}}(\boldsymbol{x}^{i}) - \boldsymbol{y}^{i})\boldsymbol{x}_{g}^{i} \qquad \textbf{(6}$$

}

For g from 0 to n

n is the number of theta(s)

D. FLOWCHART DEPICTING THE OEDS MODEL

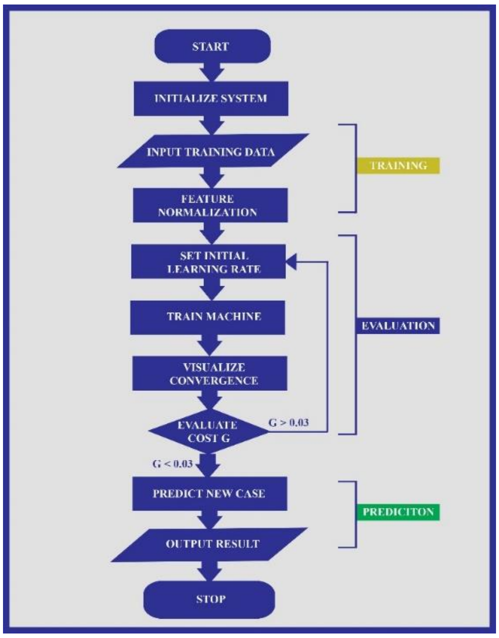

Figure 2. A flowchart of the machine learning framework for estimating Visual Acuity

E. THE OEDS ALGORITHM WITH MATLAB PSEUDOCODE

INPUT: Training data sets S, learning rate l

OUTPUT: Matrix of Theta values and VA for a new case

```
%Load sampled VA from file
S = load('datafile.txt')
%Load features in matrix X and VA in a matrix Y
X ← S(:,1);
Y ← S(:, 2:n);
no_of_samples ← length(X);
Theta ← zeros(); %set initial values of Theta
%set learning rate between 0.1 to 0.3
alpha ← 0.01;
%visualize sample data
plot(X(:,1),Y(:,2));
% scale feature, here we used mean normalization
for i = 1 : size(Y,2)
   compute X(:,i) = X(:,i) – mean(X(i)) / std(i);
end
%The gradient descent algorithm iteratively computes the cost and updates the theta values simultaneously
for repeat ← number_of_iterations;
  compute square_err ← (X * Theta) – Y;
  Theta ← Theta – ((alpha / no_of_samples) * X' * square_err);
end
%Predicting a new case
new_VA ← load('new_dataset');
compute result_of_diagnosis ← new_VA * Theta;
return theta;
fprint(result_of_diagnosis);
```

F. MATLAB IMPLEMENTATION

Table 1 shows some of the sampled datasets used to illustrate the implementation of the OEDS model using Matlab programming language. The sampled dataset had features $x_1 - x_4$ representing Age, Light Intensity, sight time, and temperature, respectively. The machine was trained to produce results consistent with the conventional estimate by a professional optometrist for a corrective lens. Table 5.1 shows a list of the data type and their value ranges.

Table 1. Variables used and their Data types

Data	***Data type***	***Range***
VA	Floating point	0.10 – 4.00
Age	Integer	000 – 130
Light Intensity	Integer	100 – 8000
Sight Time	Integer	0 - 5
Temperature	Integer	0 - 100

G. FEATURE SCALING

For improved performance of the algorithm, a dataset with large discrepancies in the ranges of values for different features need to be normalized. An important step of the OGD is the normalization of the training data to enable the algorithm to converge quickly. This is because medical data are known to vary greatly in different test cases [8]. For the above training examples, mean normalization was

used to scale the values and make them fit between the range of 1 – 10.
Thus as in [37], features were normalized as

$$Feature(x_i) = \frac{\text{feature} - \text{mean}}{\text{Largest} - \text{Lowest value}}$$

Index i is the number of features considered

H. VECTORIZATION
This step aims to use a matrix's features to implement the algorithm instead of having to iterate simultaneously through the features. Different programming languages have libraries for achieving a vectorized implementation.
The algorithm above can be implemented on any programming platform. In addition, Matlab provides visualization libraries that can monitor the performance of the GD.
To implement the algorithm, take parameters as a single vector, say theta θ so that

$$\theta = \theta - \alpha\delta$$

$$delta\ \delta = \frac{1}{m}\sum_{i=1}^{m}(h_\theta x^i - y^i) * x^i$$

Figure 3 below shows the vectorized implementation of the OEDS function in a Matlab programming environment. The gradient descent function is shown in figure 4.

```
%An implementation of the Gradient Descent in Estimating VA from a data sets
function [OEDS_VA, cost_of_iterations] = EODSAlgorithm(input_matrix_X,output_matri

cost_of_iterations= zeros(no_repeat,1);
no_of_samples = length(output_matrix_Y);
for i = 1:no_repeat

    sqrErr = (input_matrix_X * Theta) - output_matrix_Y;

    %return the minimised theta values as OEDS_VA
    Theta = Theta - ((alpha/no_of_samples) * input_matrix_X' * sqrErr);
    OEDS_VA = Theta;
    cost_of_iterations(i) = computeCost(input_matrix_X,output_matrix_Y,OEDS_VA);
end
end
```

Figure 3. An implementation of the OEDS for Estimating Visual Acuity

```
function G = computeCost(input_matrix_X,output_matrix_Y,theta)
no_of_samples = length(output_matrix_Y);
hypothesis = input_matrix_X * theta;
sqrErr = (hypothesis - output_matrix_Y).^2;
G = 1/(2 * no_of_samples) * sum(sqrErr);
end
```

Figure 4. The Function G returns the cost of the hypothesis

IV. RESULTS AND DISCUSSION

The figures in this section show the behavior of the model developed as it tries to estimate a patient's VA during the diagnosis of refractive eye defects. The model's behavior depends on the datasets used as a learning platform for the ML program. Figure 5 (a) shows the plot of the sampled VA against the intensity of light in the diagnosis environment for the first 50 datasets. The plot of the cost function at each iteration is shown in figure 5 (b). A 3D visual plot and the contour plot in figure 5(c) and 5(d) respectively elucidate how the gradient descent-powered Machine Learning system can converge to the global minimum.

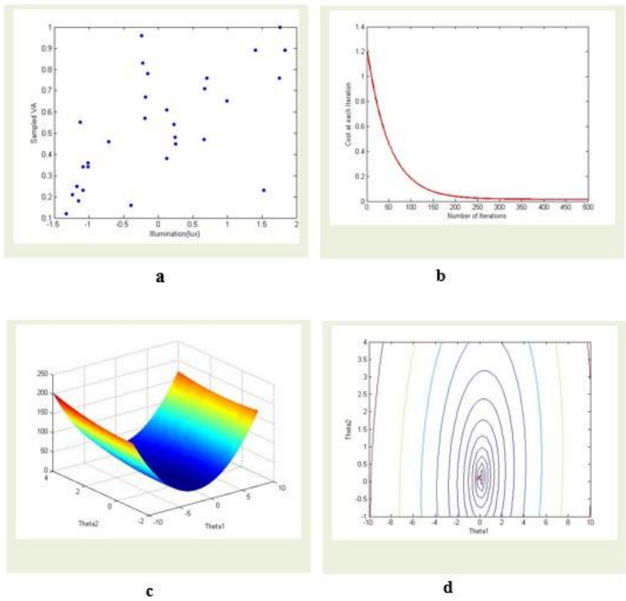

Figure 5. Plots showing the performance of the framework developed

The model was trained for 500 iterative cycles, and as shown in figure 5 (b), the algorithm arrived at the global minimum at about 300 iterations. Further iterations from this point do not seem to yield very different values; therefore, it can be concluded that the hypothesis function has been optimized, as shown in the convergence plot of the cost function against the Theta values in figure 5.1 (d). Each time the system learns, it selects a better value for the set of variable theta visualized in figure 5.1 (b). Once the training is completed, the OEDS can be used to predict VA efficiently for a case not included in the data set used for the training – this is the beauty of using a machine-learning approach.

The power of the algorithm lies in the smartness of the learning rate (alpha α, in this case). The learning rate determines the steps the algorithm would take to converge. Choosing too small a value for α might result in slow convergence while selecting too large a value of α might cause Gradient Descent convergence to fail. As we monitored the convergence of the OEDS, we changed the alpha values, and for the training set used in this case, a 0.01 learning rate seemed appropriate. The software developer has to train the machine to implement this framework; however, since the parameters are distinct in each case, the value of the learning rate might vary. Also, we have released that adding features may not necessarily improve the algorithm's performance. For greater accuracy, the number of training data sets can be increased.

Before using the OEDS to estimate a new case, the dataset has to be normalized using the mean of features and the standard deviation computed during the training. The OEDS estimated VA of 0.5 for a 20-year-old patient in a diagnosis environment of about 250lux and a room temperature of 30 degrees Celsius. Taking an arbitrary set of values for the hypothesis results in a higher cost $G(x)$. For example the vector of theta = [-1.0; 0.2; 0.1; 0.2; 0.1;0.2] resulted in G(x)= 1.229. The optimization algorithm produced a fit of a G(x) = 0.015.

V. CONCLUSION and Future Scope

Comparing the result of the OEDS versus the arbitrary hypothesis, it was evident that greater accuracy can be achieved with the OEDS. In any computation, the goal is to arrive at a model which produces results that is not very distinct from that obtained in experimental practices. In diagnosing eye-related problems, the recommendation system relay on the ability of the ML to accurately estimate the VA as a trained optometrist would. The result obtained using the approach developed in this work seems to yield approximately similar to an expert optometrist with a percentage error of less than 5%. Hence, it can be concluded that this approach will yield a more accurate estimate than most traditional approaches to estimating the VA discussed earlier.

Changing the values of the features, for example, the diagnosing device illumination or the diagnosis environment light intensity returns a different value for each coefficient. This indicates that the feature plays a vital role in the estimate. A software system that fails to account for such a factor might not achieve the optimal accuracy required for the diagnosis process. Hence, we encourage Eye diagnosis systems to adhere to best practices and to take advantage of the OEDS framework to improve the accuracy of the result.

The increase in the human population has brought along challenges to several systems. The demand for accuracy and precision in medical diagnosis caused many existing approaches to become obsolete. On the other hand, it has brought about the availability of data which enhances the ability of computers to diagnose with minimal errors. The OEDS developed in this research work is a good framework for building an Eye diagnosis system following the Visual Acuity estimation process. Software systems assist medical practitioners in diagnosing health problems and can be very beneficial in reducing the time it takes to diagnose.

We have exposed the computer scientist to the techniques required to develop a machine learning eye diagnosing system for optometrists in Clinical settings. Furthermore, this paper has shown how VA depends on geodynamic variables that each have a weight value represented by the parameter theta. Finally, the papers explained approaches that were used to improve gradient descent for the optimization objective. These include regularization, appropriately choosing the algorithm's learning rate, and evaluating the algorithm's performance by visualizing the cost function at every iteration will make GD converges faster. A Matlab implementation of the algorithm shows that the optimized GD gives an almost accurate prediction that is more reliable than a manual scalene board in the diagnosis process. Optimization is important for improving the accuracy of Machine Learning Systems [38].

Systems developed based on this model can be used in health centers where access to expensive diagnosis machines is unavailable and still produce reliable VA results for recommendation systems. In addition, Ophthalmologist, optometrists, nurses, technicians, and other health personnel can be trained to employ the OEDS-based system for a faster and more reliable diagnosis.

Even though the OEDS has produced a more accurate result than many existing manual and software systems, there is still more work to be done to improve the credibility of Eye diagnosis systems. There is a need to train the Machine Learning System with real data from real-time diagnosis and monitor the system's performance in cases of a larger dataset. A model could also be trained in several environments where factors affecting the diagnosis are liable to change. Feature extraction techniques enable the separation of data for each distinct case [39]. Some factors which have not been used for the training in this research due to data limitations include:

- The contrast of the measuring device
- The Location of the retina
- The pupil size
- Patient's medical history

An intelligent software-based system enables flexibility and ease in diagnosis. For example, measurement is restricted in the space required (20 feet or more) when using conventional chat. So to overcome this challenge, the diagnosis system should be able to dynamically adjust to deployment platforms by calculating the size of the letters and the respective distance where a patient would stand to meet up the 5 minutes of the arc, as shown in figure 6.

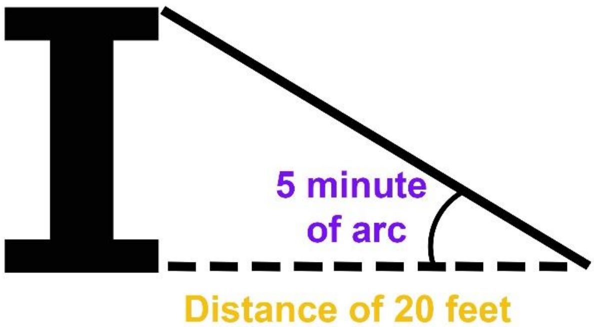

Figure 6. Five minutes of Arc requirement for accurate software diagnosis

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