Enhancing Early Detection of Diabetic Retinopathy using Machine Learning Techniques

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Abstract- The advancement of technology in the medical field has led to the development of powerful methods for the early detection of various illnesses. Diabetic retinopathy, a serious health condition caused by long-term diabetes, affects the retina and can lead to severe visual impairment. Early diagnosis is crucial for effective management and treatment. This study explores various techniques for the early detection of diabetic retinopathy using clinical data and screening images, such as pathology reports and optical coherence tomography (OCT) fundus images. The research focuses on the application of machine learning and deep learning algorithms, specifically boosting algorithms, to improve the accuracy of early diagnosis. Statistical analysis tools such as mean square error (MSE), mean absolute error (MAE), and Huber Loss (HL) are utilized to evaluate the performance of these algorithms. The findings demonstrate that a combination of indicators enhances the identification of diabetic retinopathy, providing a robust framework for its early detection.

***Keywords: Boosting Algorithms, Diabetic retinopathy, loss function, machine learning, neural networks*.**

1. INTRODUCTION

Diabetic retinopathy is a continuous confusion of diabetes mellitus. If left untreated, diabetes hyperglycemia can result in permanent vision loss. The fundamental components of the difficulties result in blurry vision and occasionally blindness. Diabetes is a long-term condition that can damage the eyes. In extreme cases, it immediately causes damage to the retinal blood vessels and causes blood to leak out of them[1]. Diabetic retinopathy poses serious risks to the retina, which can be avoided by early detection. During the early stages of retinopathy, vision loss occurs. Several machine learning algorithms are used to perform predicted analysis in the medical field. In healthcare, prescriptive analytics makes it possible to make precise forecasts and be inspired[2].

The most difficult part of getting a diagnosis is choosing treatments that will help right away. A disease's effects can be less severe if they are caught early. To create a version of the required intelligence, it is essential to investigate a variety of analysis methods and strategies. Numerous deep-learning and machine-learning algorithms are used to diagnose diabetic retinopathy in this comparison study. Several datasets that are made available to the public are used to create the forecast. Unsupervised and supervised learning are the two types of machine learning algorithms. The managed learning strategies require upheld factors and marks to make an order[3].

The automated methods known as solo learning strategies make use of multiple cycles on the preparation data to locate designs that are comparable to those of diabetic retinopathy. In addition to previous attempts to diagnose diabetic retinopathy, the suggested method makes use of neural networks, machine learning, and deep learning techniques [4]

- The proposed paper is focused on conducting a comprehensive study on diabetic retinopathy detection using boosting algorithms in machine learning models.
- The study is specifically focused on the study on the hybrid concept provided by the boosting algorithms.

The rest of the paper is formulated as a Literature study in section 2. Various methodologies are discussed in Section 3. Different types of boosting algorithms in section 4. Followed with conclusion and future work is rovided.

2. LITERATURE SURVEY

G. Kumar et al., 2020A capsule network-based method for identifying diabetic retinopathy was developed by the author. To assess the framework for the most present-day handling draws near, a brain network reasonable model diabetic retinopathy demonstrative organization is sent. The accuracy of the 1265 photos in the research dataset is 80.59%, which is higher than the higher grade of DRDNET comparisons.

S. Prabha et al.,(2020) Using the Taylor core method and the STARE and DRIVE datasets, image analysis reveals retinopathy. A machine learning algorithm is used to extract retinal blood vessels. The technology that was developed as a linear approach for the early diagnosis of diabetic retinal and irreversible blindness was discussed by the author. It is currently being studied. Early damage to the retina's blood vessels was the first of the four most common outcomes of diabetic retinopathy. The Hough transform can be applied to optical tomography (OCDopti) images to make precise predictions about blood vessels.

Mrityunjaya et al., (2020)The progression of retinopathy is significantly influenced by AI calculations. the aid in protecting the system from diabetic retinopathy, which led to early vision loss, or the early identification of changes in the images of the retina. In this case, retinal pictures can be taken with smartphones. The framework assessed the pictures gathered through cell phones, the backend retinopathy discovery program utilizing the K closest neighbor (KNN) calculation. Despite the discovery of the disorder, the enhanced construction is surveyed utilizing the Kth pertinent neighbor approach...

X. Li et al., (2021)The identification of diabetic retinopathy is being improved through the utilization of the interactive cell supervisor learning strategy. A self-supervised learning algorithm and a publicly accessible dataset were used in the author's demonstration of a system. The area under the curve has an accuracy of 4.2%. Pathology myopic age-related retinopathy is identified and diagnosed using a supervised method. Fundus images are used to create the original strategy.

X. Li et al., (2020)This section discuss self-supervised methods for learning relevant features. Retinopathy is the focus of the multimodal data analysis for identifying retinal diseases. The neural network-categorized retinal disease dataset was obtained from a publicly accessible source. The presented method improves the multi-modality feature's accuracy for making new predictions and takes into account the characteristics of retinal images..

S. K. Reddy et al., (2021) In this study, the author presented a method for gathering images of the retinal fundus from the Kaggle dataset to identify changes in retinal imaging caused by long-term diabetes. The machine learning algorithm may be able to accurately predict illnesses or anomalies in medical images by utilizing characteristics gathered from medical images. Without proper treatment, diabetics run the risk of losing their vision. The author demonstrated a method that demonstrates the location and severity of diabetes' delay in detection.

3.METHODOLOGY

3.1 GENERAL STRUCTURE OF RETINOPATHY CLASSIFICATION

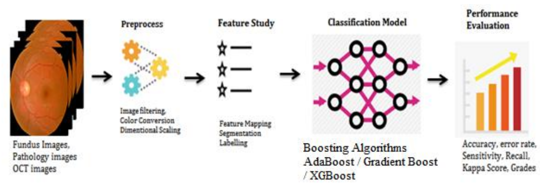

Fig 1. The general structure of Retinopathy classification

Fig 1. Shows general structure of Retinopathy classification using boosting algorithm is depicted here. The architecture consists of pre-processing, Image filtering, Color conversion, and dimension scaling block to enhance the input image. Fundus images are collected from the optical lab in which pathology data is given. The feature mapping process segment and label the pattern to unique weight. Various kinds of Boosting algorithms are available. Before fetching the data into Boosting algorithm, the feature data are split into a training set of 80%, and a testing set of 20%. In certain cases, validation data also get separated. various publicly available benchmark datasets are considered for unique classification. Some of the commonly considered datasets are Kaggle APTOS, DIARET(DB1), DIARET(DB0), MESSIDOR, EyePACKS, IDRiD, and PIDD utilized for early prediction research.

4. BOOSTING ALGORITHMS

By utilizing a variety of Machine Learning strategies to improve the model's accuracy, boosting is an ensemble learning strategy that transforms weak learners into strong learners.

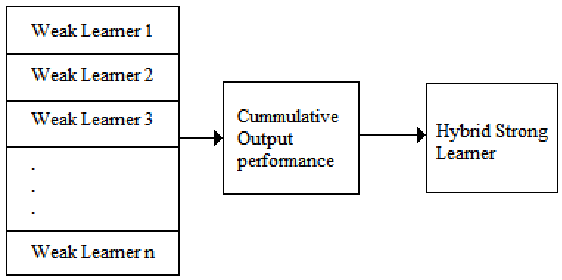

Fig 2. Hybrid functionality of Boosting algorithms

Fig 2. Shows the hybrid functionality of boosting algorithm. Ensemble learning improves the viability of an AI model by blending numerous students. Models produced by this method of learning are more precise and effective than models. As a result, ensemble methods are used to meet market requirements and produce accurate predictions. These kinds of boosting algorithms are necessary for the models of artificial intelligence.

4.1 Ensemble learning

Ensemble learning can be performed in two ways. Boosting algorithm, also known as the sequential ensemble technique, which during the training process produces weak learners consecutively. The performance is directly impacted by the training process. When the sample data's previous performance is given more weight, the model produces better results. The process enhances the AdaBoost method based on each instant's results. During the learning phase of retinal images, the weak trainees are created concurrently through the parallel ensemble technique, also known as bagging. Parallel training of the number of initial learners with built-from-scratch data sets can improve model performance. The Random Forest algorithm is bagged.

The idea of creating numerous weak learners and combining their predictions into a single strong rule is the foundation of the boosting method. To foster these powerless standards, base AI strategies are applied to unmistakable informational collection circulations. With each iteration, these algorithms produce weak rules. The weak learners are combined after several cycles to produce a strong learner that can predict an expected outcome with increasing accuracy. The base algorithm collects the data and gives each sample observation gathered by the initial process the same weight.It is determined which basic learning projections are incorrect. The learning algorithm is given more weight in the subsequent generation for these incorrect forecasts.

4.2 Adaptive Boosting Model

Boosting algorithms are highly utilized in classification and regression problems. In complex data patterns where in-depth analysis is required, the role of boosting algorithm increases. Various types of boosting algorithms are utilized commonly in practice. Commonly used algorithms are Adaptive Boosting or AdaBoost, Gradient Boosting, XGBoost, etc.

- AdaBoost is a hybrid algorithm that combines multiple weak readers into a single strong learner.Each piece of information receives the same weight when determining the initial decision point.
- Any incorrectly identified observations are given greater weight when the early decision's findings are evaluated. After that, a new decision stump is made by treating observations that have higher weights as having more significance.
- To negotiate the classification, weights are always added in the process. This procedure is repeated until both the training data and the testing data are correctly categorized. Any items that are incorrectly categorized receive extra weight.
- Adaboost can be used for both classification and regression problems, but the classification of problems with less fitting problems is the most common application.

4.3 Gradient Boosting Model

The successive ensemble learning process is also utilized by the Gradient Boosting algorithm. In this scenario, the first learners are designed so that the next base learner is always better than the one before it. Consequently, the model's performance improves with each iteration.

Gradient boosting introduces a new model with a weak classifier to minimize the nonlinear function to maximize the previous learner's loss function but does not raise weights for miscategorized results.

The significant objective is to correct the anticipated mistakes delivered by the earlier investigation model. The three main components of this kind of boosting algorithm are as follows: ought to be improved capabilities for processing.

Engaged in informal activities that result in the creation of strong learnersclassifiers and forecasts. The loss function is regularized with a novel system.

4.4 XGBoost Model

The XGBoost technique is a high-level variation of the gradient boosting approach that offers deep, relatable pattern analysis. The Distributed Machine Learning Community includes the XGBoost algorithm, also known as the extreme boost algorithm. To improve performance, a variety of hybrid strategies are developed here.

The main objective of this calculation is to speed up and make calculations more accurate. The result is computed at a slower rate because the Gradient Descent Boosting method evaluates the data set in stages. Consequently, XGBoost is utilized to significantly increase the model's performance.

The goals of XGBoost are accomplished with high model efficiency and computational speed. The most important features of XGBoost are as follows:

• It builds decision trees while using distributed computing

• The system uses distributed analysis to analyze large and complex models

• The system can be used for small analyses as well as for large, complex datasets. enhancing the cache to make the most of the available resources.

As a result, the following were the various methods for improving machine learning: In the following section, we will use an example to demonstrate how Python can be used to create techniques for boosting to keep things interesting.

4.5 Evaluation methods

A misfortune capability in AI shows the execution of the ML model that predicts the expected outcome, or the ground truth. The actual anticipated value and the value of our model's output will serve as the basis for feeding the loss function. The misfortune, which is proportional to the prediction system's outcome, is the result of the unfortunate power.

Mean Squared Error (MSE)

The Mean Squared Mistake (MSE) is perhaps the most un-complex and most normal blunder capacity, and it is regularly shown in early simulated intelligence classes. The MSE is calculated by squaring the difference between the model's prediction and the actual result and averaging it to the data point's maximum expectation.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - yc_i)^2 \tag{1}$$

Mean Absolute Error (MAE)

The definition of the Mean Absolute Error (MAE) differs significantly from that of the MSE, producing opposite features. By averaging the absolute value of the difference between the model predictions and the given actual input across the entire dataset, the MAE is derived.

$$L(y, f(x)) = \{\frac{1}{2}(y - f(x))2\}, \{\delta \mid y - f(x) \mid -0.5\delta^2 \tag{2}$$

Huber Loss

The Huber Misfortune arrives at balance by blending the MSE and MAE values, furnishing ID of best arrangement with both functions. The following piecewise capability enables the system to characterize it.

$$MAE = \frac{1}{N} \mid \sum_{j=1}^{N}(y_j - yc_j) \mid \tag{3}$$

Table 1. Comparison of boosting algorithms on Retinopathy detection

S.No	Reference	Research scheme	Methodology	Statistical Measures
1	S. Roychowdhury et al., (2014)	DR classification using ML	GMM, SVM, KNN	53.16% specificity, 96% sensitivity, 51% specificity, and 0.875 AUC
2	H. Mustafa et al., (2022)	DR severity classification using a boosting algorithm	PCA, Random Forest	ACC=95.58%
3	B. Dashtbozorg et al., (2018)	Retinal microaneurysms detection	Local convergence index features (LCI)	Sensitivity=0.407
4	Washburn et al., (2018)	DR classification using AdaBoost	AdaBoost algorithm	ACC=98.4%
5	Li W et al., (2021)	DR classification using XGBoost	XGBoost algorithm	AUC=0.90
6	R. Bhuvaneswari et al., (2021)	DR classification Hybrid Boost Algorithm	Ensemble Boost algorithm	ACC=95.8%

Table 1. Shows comparison of boosting algorithm on diabetic retinopathy detection. Various algorithms are discussed here, in which the boosting algorithms play an optimum role in the classification of diabetic retinopathy as well as in generating a model with lightweight architecture. The Boosting algorithms such as AdaBoost, gradient Boost, and XGBoost algorithm is compared over here with the comprehensive data collected from existing articles. Further, the research scope towards the algorithm selection for diabetic retinopathy classification is studied here. Utilization of Boosting process in novel algorithms improves the performance of the model in terms of accuracy, sensitivity, reduction of error, etc.

CONCLUSION

To break the cycle of getting worse, chronic diseases need to be treated early. An important concern is a sign identifying diabetic retinopathy early. Diabetes is a long-term condition that gradually and directly affects the body's organs. The current study, which takes into account a variety of existing advancements based on the diabetes area of detection, takes into account the technique and performance measurements that have been accomplished or mentioned in prior studies. The proposed study asserts that machine learning algorithms, specifically boosting algorithms, have a significant impact on the early diagnosis of diabetic retinopathy. It is proposed that the research be expanded to include a generic set of network models that, through iterative learning from a variety of datasets, can accurately classify diabetes mellitus. As the data set gets better, the built model will be checked and proven.

REFERENCES

[1] J. D. Labhade, L. K. Chouthmol, and S. Deshmukh, "Diabetic retinopathy detection using soft computing techniques," 2016 International Conference on Automatic Control and Dynamic Optimization Techniques (ICACDOT), 2016, pp. 175-178, doi: 10.1109/ICACDOT.2016.7877573.

[2] A. T. Nagi, M. Javed Awan, R. Javed and N. Ayesha, "A Comparison of Two-Stage Classifier Algorithm with Ensemble Techniques On Detection of Diabetic Retinopathy," 2021 1st International Conference on Artificial Intelligence and Data Analytics (CAIDA), 2021, pp. 212-215, doi: 10.1109/CAIDA51941.2021.9425129.

[3] B. Dashtbozorg, J. Zhang, F. Huang and B. M. ter Haar Romeny, "Retinal Microaneurysms Detection Using Local Convergence Index Features," in IEEE Transactions on Image Processing, vol. 27, no. 7, pp. 3300-3315, July 2018, doi: 10.1109/TIP.2018.2815345.

[4] S. Roychowdhury, D. D. Koozekanani and K. K. Parhi, "DREAM: Diabetic Retinopathy Analysis Using Machine Learning," in IEEE Journal of Biomedical and Health Informatics, vol. 18, no. 5, pp. 1717-1728, Sept. 2014, doi: 10.1109/JBHI.2013.2294635.

[5] H. Mustafa, S. F. Ali, M. Bilal and M. S. Hanif, "Multi-Stream Deep Neural Network for Diabetic Retinopathy Severity Classification Under a Boosting Framework," in IEEE Access, vol. 10, pp. 113172-113183, 2022, doi: 10.1109/ACCESS.2022.3217216.

[6] B. Dashtbozorg, J. Zhang, F. Huang and B. M. ter Haar Romeny, "Retinal Microaneurysms Detection Using Local Convergence Index Features," in IEEE Transactions on Image Processing, vol. 27, no. 7, pp. 3300-3315, July 2018, doi: 10.1109/TIP.2018.2815345.

[7] Washburn, Praveen & Mahendran, &Dhanasekharan, & Periyasamy, &Murugeswari,. (2020). Investigation of severity level of diabetic retinopathy using adaboost classifier algorithm. Materials Today: Proceedings. 33. 10.1016/j.matpr.2020.03.199.

[8] F. Saeed, M. Hussain and H. A. Aboalsamh, "Automatic Diabetic Retinopathy Diagnosis Using Adaptive Fine-Tuned Convolutional Neural Network," in IEEE Access, vol. 9, pp. 41344-41359, 2021, doi: 10.1109/ACCESS.2021.3065273.

[9] Jalil, Z. et al. (2022) “Covid-19 related sentiment analysis using state-of-the-art machine learning and Deep Learning Techniques,” Frontiers in Public Health, 9. Available at: https://doi.org/10.3389/fpubh.2021.812735.

[10] Li W, Song Y, Chen K, Ying J, Zheng Z, Qiao S, Yang M, Zhang M, Zhang Y. Predictive model and risk analysis for diabetic retinopathy using machine learning: a retrospective cohort study in China. BMJ Open. 2021 Nov 26;11(11):e050989.

doi: 10.1136/bmjopen-2021-050989. PMID: 34836899; PMCID: PMC8628336.

[11] Shen Z, Wu Q, Wang Z, Chen G, Lin B. Diabetic Retinopathy Prediction by Ensemble Learning Based on Biochemical and Physical Data. Sensors. 2021; 21(11):3663. https://doi.org/10.3390/s21113663.

[12] R. Bhuvaneswari and S. Ganesh Vaidyanathan. 2021. Classification and grading of diabetic retinopathy images using mixture of ensemble classifiers. J. Intell. Fuzzy Syst. 41, 6 (2021), 7407–7419. https://doi.org/10.3233/JIFS-211364.

[13] K., Shankar., Abdul, Rahaman, Wahab, Sait., Deepak, Gupta., S., K., Lakshmanaprabu., Ashish, Khanna., Hari, Mohan, Pandey. (2020). Automated detection and classification of fundus diabetic retinopathy images using synergic deep learning model. Pattern Recognition Letters, 133:210-216. doi: 10.1016/J.PATREC.2020.02.026.