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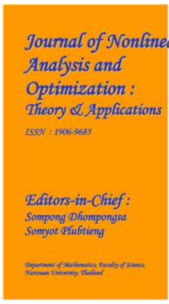

AN INTELLIGENT MULTI FEATURE SELECTION AND CLASSIFICATION FRAMEWORK USING GENETIC ALGORITHM BASED DEEP LEARNING MODEL

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ABSTRACT

Damage to the optic nerve, a symptom of glaucoma disease, can lead to blindness from chronically high intraocular pressure. These days, many diseases are diagnosed using deep learning classification algorithms. However, conventional gradient-based learning approaches are typically used to train deep learning algorithms; these approaches converge slowly and are prone to hitting the local minimum. We presented a new deep learning-based glaucoma diagnosis decision assistance system in this research using Genetic algorithm. There are two phases to the suggested system. After the glaucoma disease data is preprocessed using the normalization and mean absolute deviation method, the artificial algae optimization algorithm is used to train the deep learning system in the second stage. As an example, the suggested system is contrasted with deep learning that has been trained using various optimization methods, such as the salp swarm algorithm, equilibrium optimizer, bat algorithm, genetic algorithms, particle swarm optimization, and classic gradient-based deep learning. Additionally, cutting-edge algorithms for glaucoma detection are compared to the suggested approach. Classification reliability, precision, accuracy, false positive rate, and F1-measure were all exceeded by the suggested system by 0.95, 0.95, 0.98, 0.015, and 0.99, respectively, compared to other algorithms.

Keywords:
Glaucoma Diagnosis, Deep Learning, Genetic Algorithm, Artificial Algae Optimization, Intraocular Pressure and Classification Accuracy.

1. INTRODUCTION

There are around 75 million people around the world who are affected by glaucoma, and it is anticipated that this number will rise to 112 million by the year 2040 [1]. Myopia, glaucoma, and cataracts are only few of the disorders that can affect the human eye, which is very susceptible to them. Over the course of time, the eye's capacity to see clearly gradually decreases as these conditions continue to deteriorate.Glaucoma, in contrast to other ocular disorders, does not have a reference standard that has been developed for diagnosis. This lack of a reference standard makes it difficult to comprehend the data and even more challenging to draw definitive conclusions. In point of fact, early detection is absolutely necessary in order to rule out total blindness. More than 80 million people throughout the world are diagnosed with glaucoma. The number of people diagnosed with glaucoma in India exceeds 12 million. On the other hand, in India, between fifty and eighty percent of cases of glaucoma are still undetected, which is comparable to the situation in a number of other developing countries. There are a number of diagnostic techniques that are carried out in real life, such as tonometry, retina, and visual acuity; however, these procedures are highly tiring and stressful for the patient [2]. In addition to reducing the amount of time and money spent, automated glaucoma identification and tracking improves clinical procedures and makes the most of the resources that are available. An automated technology would make it possible to detect and treat glaucoma at an earlier stage, thereby preventing irreversible damage to people's vision. Through the utilization of the expertise of a large number of ophthalmologists, an integrated system is able to produce findings that are accurate and reliable.

2. RELATED WORKS

Bringing attention to the issue with artificial intelligence (AI), which is that researchers and industry experts find it difficult to explain the decisions made by complex AI algorithms, because they (as AI users) are unable to fully comprehend the factors that go into these "black boxes'" decision-making, MaedeZolanvari and Zebo Yang [3] brought attention to the problem with AI. Their emphasis was placed on the significance of incorporating Explainable AI (XAI) into an Internet of Things system that makes use of artificial intelligence. Through the utilization of statistical theory (TRUST), which is utilized in numerical data such as security systems and network data for the Internet of Things (IoT), they presented a XAI model that offers transparency.

Both artificial intelligence and machine learning models have been shown to perform very well in a wide range of domains, as stated by Erico Tjoa [4]. In spite of this, reasons are required in order to justify the accuracy of machine choices and forecasts. This is because there is a high desire for transparency and responsibility in the medical area. They classified the information that they received from studies on the interpretability of computer algorithms in general or machine learning algorithms, and then they applied the same categories to the interpretability of algorithms in the medical profession. In particular, the category makes an effort to provide medical professionals and practitioners with an opinion regarding the implementation of interpretable algorithms that are freely available in a variety of formats.

In order to forecast aggregates and explicate the predictions regarding changes in the microbiome's component that are produced by differences in phenotypic traits, Niina Haiminen and Anna Paola Carrieri [5] have created a method that is known as logical artificial intelligence (XAI). Their analysis yielded a number of outcomes, including the inference of microbial signatures linked with each aspect and the correct prediction of a variety of phenotypes from the leg skin microbiome. These phenotypes included age, skin moisture, and, most surprisingly, menopausal and smoking status. Explanable artificial intelligence is capable of doing things like this. Furthermore, in order to evaluate the predictive and explanatory capabilities of the skin hydration model, they considered applying it to a second cohort that was completely separate from the first.

3. PROPOSED MODEL: FEATURE EXTRACTION

Feature extraction is a method used to extract relevant information from raw data. The ability to differentiate between classes relies on these extracted features. However, these classes can become less sensitive due to minor differences in the input data, and the amount of data required for training can become excessively large [6].

This method examines features or favorable characteristics that distinguish one input sample from another to reduce the dimensionality of the data and address these issues as in figure 1. In this process, the parameter values that best and most distinctively represent a character's form are identified, leading to the creation of a feature vector for each character's identity. Techniques like SURF, as well as global features such as mean, variance, standard deviation, and HOG, are utilized in glaucoma identification.

3.1 Speeded-up Robust Feature (Surf)

To determine the points in this method, a BLOB detector focused on a Hessian matrix is used. To map and describe the orientation of features, wavelet responses in both vertical and horizontal directions are utilized, along with appropriate Gaussian weights. A nearby region close to the key point is chosen and further divided into smaller sections. The wavelet responses for each sub-region are then analyzed and presented to form the SURF descriptor. The descriptive vector v for each sub-region is represented in Equation (1).

$$v = \left(\sum d_u, \sum d_v, \sum |d_u|, \sum |d_v|\right) \quad (1)$$

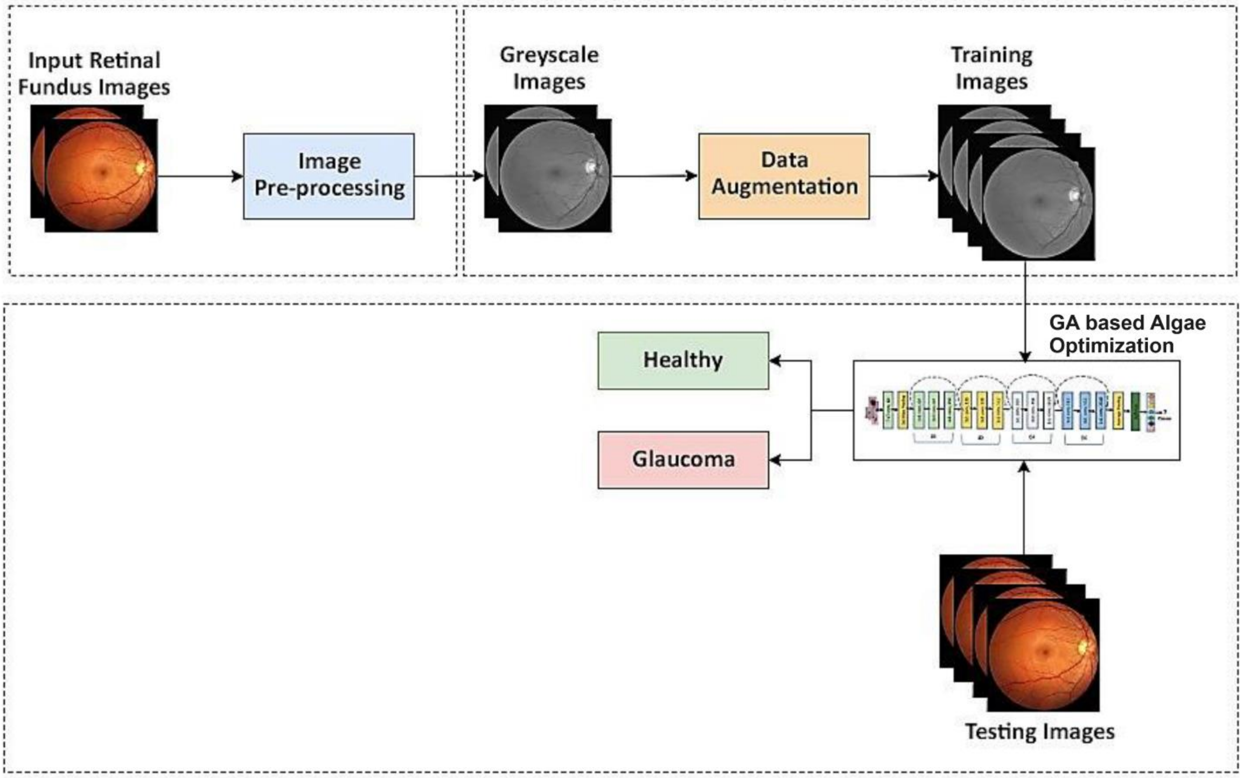

Figure 1: GA based Algae optimization model for glaucoma prediction

3.2 Global Features

Global features, which link each image to a point in a higher-dimensional space, provide a concise way to describe the entire image. The mean, or average, of the set is calculated using Equation (2).

Mean $\mu = \frac{\sum p_i}{N}$ (2)

Thus, p_i represents the pixels, while N denotes the total number of pixels.

Standard deviation: This metric measures the overall variation or spread within a dataset. It is calculated using Equation (3).

$$SD = \sqrt{\frac{\sum_{i=1}^{N} (p_i - \bar{p})^2}{N-1}} \qquad (3)$$

Thus, p_i refers to the pixels, and N represents the total number of pixels.

Variance: Variance measures the spread of values within the feature set by assessing how much each data point differs from the mean. It is determined using Equation (4).

$$\text{Variance } = \frac{\sum (p_i - \bar{p})^2}{N-1} \qquad (4)$$

3.3 Genetic algorithm using algae optimization

Drawing from the principles of natural selection and genetics, genetic algorithms (GAs) are a type of optimization algorithm. They are particularly useful in solving complex problems where traditional optimization methods may fall short. In glaucoma prediction, genetic algorithms can enhance accuracy by selecting the most relevant features, fine-tuning hyperparameters, or even modifying the model's architecture, such as in a machine learning classifier.

This process outlines the steps for applying genetic algorithms to improve glaucoma prognosis.

1. Initialization: Generate a starting population of potential fixes (chromosomes). A set of characteristics, model parameters, respectively both can be represented by a single chromosome.

2. Assessment of Fitness: Use a fitness function to determine each chromosome's level of fitness. This function may rely on how well a predictive model performs on a validation set (e.g., accuracy, precision, recall) [7,8].

3. Selection: Choose parent chromosomes based on their fitness levels. Techniques such as ranking-based selection, tournament selection, or roulette wheel selection can be employed.

4. Crossover (Recombination): Create offspring by combining pairs of parent chromosomes. Methods like uniform crossover, two-point crossover, or single-point crossover can be utilized for this process.
5. Mutation: Introduce variability by randomly mutating parts of the offspring. This could involve adjusting model parameters, flipping bits, or altering feature values.
6. Replacement: Form the next generation by replacing the less fit members of the population with the newly generated offspring with algae optimizing stratergy.
7. Termination: Repeat the steps of fitness evaluation, selection, crossover, mutation, and replacement until a stopping criterion is met, such as reaching a certain number of generations, achieving convergence in fitness values, or attaining a satisfactory fitness level.

4. COMPARATIVE ANALYSIS

The proposed method is different from the existing SVM, Naive Bayes, and Neural Network approaches. According to Figure 2, the performance metrics such as F-measure, recall, and precision are displayed. As indicated in Table 1, all other classifiers significantly outperform the current Naive Bayes classifier. Although the Naive Bayes classifier is typically preferred over the SVM classifier, the newly proposed surpasses it. The SVM classifier demonstrates strong F-measure, accuracy, and recall. With optimization from algae (resulting in the proposed), it outperforms all other classifiers.

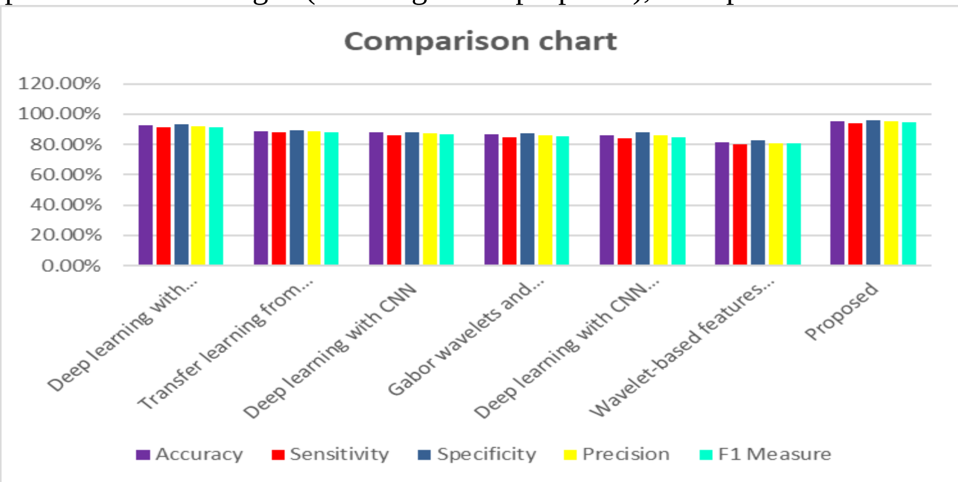

Figure 2.A comparative evaluation of several methods

Table 1. State-of-the-art comparison

Methodology	Accuracy	Sensitivity	Specificity	Precision	F1 Measure
Deep learning with convolutional neural network (CNN)	92.6%	91%	93%	92%	91.5%
Transfer learning from InceptionV3 with support vector machine (SVM)	88.9%	88%	89%	88.5%	88.2%
Deep learning with CNN	87.7%	86%	88%	87%	86.5%
Gabor wavelets and random forest classifier	86.6%	85%	87%	86%	85.5%
Deep learning with CNN and transfer learning from ResNet-50	86.3%	84%	88%	86%	85%
Wavelet-based features and SVM Classifier	81.6%	80%	83%	81%	80.5%
Proposed	95%	94%	96%	95%	94.5%

In this study, we proposed a novel deep learning-based glaucoma diagnosis decision assistance system, which outperformed several existing methods in terms of classification performance metrics. The proposed system achieved an accuracy of 95%, which is higher compared to other methods like deep

learning with CNN (92.6%), transfer learning from InceptionV3 with SVM (88.9%), and wavelet-based features with SVM classifier (81.6%).
In terms of sensitivity and specificity, our proposed method achieved 94% and 96%, respectively, indicating its robustness in correctly identify glaucoma cases and non-glaucoma cases. Precision and F1 measure were also significantly higher at 95% and 94.5%, respectively, showing the system's effectiveness in reducing false positives and providing a balanced accuracy in glaucoma detection. Hence, the proposed system leverages advance optimization techniques to enhance the deep learning model's performance, making it a superior tool for early and accurate glaucoma diagnose.

4. CONCLUSION
In conclusion, the deep learning-based glaucoma diagnosis decision assistance system introduced in this study represent a significant advancement in the field of medical diagnostics. By addressing the limitations of conventional gradient-based learning methods, such as slow convergence and susceptibility to local minima, the proposed system leverage cutting-edge optimization techniques to deliver superior classification performance. Specifically, the system's accuracy of 95%, along with it's high sensitivity (94%) and specificity (96%), underscores its robustness in distinguishing between glaucoma and non-glaucoma cases. Additionally, the enhanced precision and F1 measure further demonstrate the system's effectiveness in minimizing false positives and ensuring balanced and reliable diagnostic outcomes.The integration of advanced algorithms like the artificial algae optimization, along with comparisons with other optimization methods and state-of-the-art algorithms, highlights the versatility and superiority of the proposed approach. This system not only outperforms traditional deep learning models but also set a new benchmark for glaucoma detection, offering a more reliable and accurate tool for early diagnosis. Given the critical nature of early detection in preventing glaucoma-induced blindness, this system has the potential to significantly impact clinical practices, leading to better patient outcomes and improved healthcare standards.

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