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SVM based Prediction Model for Primary Open-Angle Glaucoma with Optic Nerve Vasoconstriction Based on Age-Related Degeneration & Environmental Pollution

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Abstract: This research aims to develop a predictive model for primary open-angle glaucoma (POAG) using the Support Vector Machine (SVM) algorithm. The study integrates age-related degeneration, pollution effects on eyes, and vasoconstriction at the optic nerve head. Diverse age groups will be analyzed using clinical records, imaging data, and environmental parameters. SVM will identify patterns and evaluate features such as optic nerve head morphology, intraocular pressure, age, pollution exposure, and vascular reactivity. The proposed model seeks to enhance early POAG detection and provide insights into the association between pollution and glaucoma. Anticipated outcomes include a robust SVM- based prediction model for POAG, facilitating risk assessment and early intervention. This research contributes to ophthalmology and machine learning, enabling personalized glaucoma risk assessment and targeted healthcare interventions.

Keywords: *Support Vector Machine, Primary Open Angle Glaucoma, Age related Degeneration, Vasoconstriction, Optic Nerve Head Morphology, Intraocular Pressure, Vascular Reactivity, Environmental Pollution, Hyper Plane*

1. Introduction

Primary open-angle glaucoma (POAG) is a prevalent and progressive eye disease characterized by the gradual damage to the optic nerve, leading to irreversible vision loss. While age-related degeneration is a known risk factor for POAG, recent research has also focused on the potential impact of environmental pollution on ocular health[1][2]. In several areas, cities, and countries, air pollution has become a significant concern, with growing evidence linking it to various health problems. The influence of air pollution on glaucoma incidence has garnered attention due to its potential role in aggravating the disease's progression. Particulate matter (PM), nitrogen dioxide (NO2), and other pollutants present in the air may have adverse effects on the ocular surface, optic nerve, and overall ocular health[3][4].These pollutants can induce oxidative stress, inflammation, and vasoconstriction, ultimately impacting the optic nerve head and retinal blood vessels.

Blood vessels, including arteries and veins, play a crucial role in maintaining healthy ocular function. Impairment of blood flow due to pollution-induced vascular changes can affect the optic nerve's health and lead to glaucomatous damage[5]. Vasoconstriction of these vessels may result in reduced perfusion, leading to ischemia and hypoxia in the optic nerve head, further contributing to glaucomatous damage. The impact of pollution on glaucoma prevalence may vary depending on the local environment[6]. Areas with high levels of particulate matter and NO2 are likely to have a more significant influence on ocular health. Identifying regions with elevated pollutant concentrations can aid in targeting preventive measures and public health interventions [7].

Early identification of glaucoma is crucial to initiate timely treatment and preserve vision [8][9]. Detecting glaucoma at its earliest stage, known as the pre-perimetric stage, can significantly improve patient outcomes. At this stage, individuals may not experience noticeable symptoms or vision loss, making regular eye screenings and predictive tools like SVM essential for early detection. Glaucoma progression can be categorized into different risk stages based on the severity of the disease and the degree of optic nerve damage [10]. These stages include early moderate, and advanced glaucoma. SVM's predictive capabilities can aid in identifying subtle changes in blood vessel morphology and optic nerve head appearance that can serve as early indicators of glaucoma development, even in the pre-perimetric stage. By leveraging SVM and analyzing data encompassing age-related degeneration, pollution effects, and vascular changes, researchers can develop accurate prediction models for glaucoma [9]. Such models can not only help identify vulnerable populations in areas with high pollution levels but also provide valuable insights into glaucoma progression, allowing for

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more personalized treatment plans [11][12].

1.1 Related Work

Seong Jae Kim, et al., have developed different machine learning models for diagnosis of Glaucoma based on retinal nerve fibre layer thickness and visual field . They developed four machine learning models viz., C5.0, Random Forest, KNN and SVM models. They found that, the prediction of Random Forest model is high compared to other models [1]. Zvia Burgansky-Eliash, et al, have used Linear Discriminant Analysis, Support Vector Machine, Recursive Partitioning, Regression Tree, Generalized Linear Model and Generalized Additive Model in detecting the Optical Coherence Tomography (OCT) Glaucoma detection [19]. Dey, A.; Bandyopadhyay, S.K have applied image processing techniques on fundus images for analyzing Glaucotomous and non-glaucotomous eye [2]. For this, they have used Support Vector Machine classification method for analyzing the images [3]. Similar kind of research has been done by Chao-Wei Wu, et al., for the detection of Glaucoma using SVM classification method on spectralis tomography [4]. Guangzhou An, et al, have developed a machine learning based algorithm using CNN model for Glaucoma diagnosis in patients with open angle glaucoma based on optical coherence tomography data [5]. Barros. D.M.S., Moura, et al have reviewed supervised methods for glaucoma screening in retinal images. They observed that, it is possible to build a system using machine learning for glaucoma analysis [4]. Oh S, Park Y et al, have developed a prediction model using four different machine learning algorithms viz., the SVM, C5.0, Random Forest and XGBoost models. They observed that XGBoost model gave higher performance when compared with other models in predicting the disease. Infact, they have used explainable AI for the first time in diagnosing the disease [15]. Akter, N., Fletcher, J., Perry, S. et al. have used diagnostic features from both Normal and glaucomatous patients based on structural, functional and demographic and risk factors and optimized the features to detect the glaucoma using machine learning algorithms [11][6].

2. Method

2.1 Features of Support Vector Machine

SVM is a powerful supervised machine learning algorithm used for classification and regression tasks. SVM is particularly well-suited for solving binary classification problems, and it can also be extended to handle multi-class classification tasks. The fundamental idea behind SVM is to find an optimal hyperplane that best separates the data points of different classes in the feature space. This hyperplane acts as a decision boundary, dividing the data into two classes. The objective is to maximize the margin between the two classes, which is the distance between the hyperplane and the nearest data points from each class. Given below are some important concept of SVM and its usage in the current research.

2.2 Hyperplane and Margin:

The hyperplane in SVM is a subspace of the feature space that has one dimension less than the original space. In a two-dimensional feature space (for example, with two features), the hyperplane is a straight line. In a higher-dimensional space, the hyperplane becomes a hyperplane (a flat surface). The optimal hyperplane is the one that has the maximum margin, which is the region between the two classes where no data points are present. SVM aims to find the hyperplane that maximizes this margin.

2.3 Support Vectors, Kernel trick and Softmargin:

Support vectors are the data points closest to the hyperplane and have the most significant influence on determining the position and orientation of the hyperplane. The margin is defined by these support vectors, and any changes to their position could alter the orientation of the hyperplane. In the real time scenario, the data points may not be linearly separable in the original feature space. The kernel trick is a mathematical technique used in SVM to map the data into a higher-dimensional space, where it becomes linearly separable. Commonly used kernels include the linear kernel, polynomial kernel, radial basis function (RBF) kernel, and sigmoid kernel. In real-world datasets, it is often challenging to find a hyperplane that perfectly separates the two classes due to noise and overlapping data. SVM allows for a soft margin by introducing a penalty for misclassifications

2.4 Prediction and Classification:

Once the optimal hyperplane is identified, new data points can be classified based on their position relative to the hyperplane. Data points above the hyperplane will be classified into one class, while points on the other side will be classified into the other class.

In summary, Support Vector Machine (SVM) recognizes patterns and determines the order by finding an optimal hyperplane that maximizes the margin between two classes in the feature space. It identifies support vectors that play a critical role in defining the hyperplane's position and orientation. SVM can handle linearly inseparable data by using the kernel trick to map data into higher-dimensional spaces. With the ability to handle soft margins, SVM can effectively handle real-world datasets with some overlapping data points or noise.

This proposed research explores the potential impact of environmental pollution on the rising cases of glaucoma, particularly in areas with high pollution levels. The use of SVM as a prediction tool offers the potential to identify subtle vascular changes and optic nerve head characteristics that could indicate the presence of glaucoma or the risk of its future development. Through early detection and intervention, we can take significant strides in mitigating the burden of this sight-threatening disease. By considering blood vessel flow, arteries, and veins, researchers can gain a comprehensive understanding of how pollution affects ocular health. Early identification at the pre-perimetric stage and categorizing glaucoma into risk stages enable timely intervention and improved patient outcomes. When applied to the context of identifying blood vessel patterns in the eye retina and their relationship to primary open-angle glaucoma (POAG), SVM can play a crucial role in predicting and understanding the disease. The following information below gives the reason on how SVM is related to identifying blood vessel patterns and its connection to the development of POAG.

2.5 Pattern Recognition with SVM:

SVM aims to find a decision boundary (hyperplane) that maximizes the margin between data points of different classes. In the case of identifying blood vessel patterns in the retina, SVM can learn to distinguish between healthy blood vessel patterns and those associated with POAG.

2.6 Retina Blood Flow and Vascular Changes:

Blood vessels in the retina play a vital role in supplying oxygen and nutrients to the eye's tissues. Changes in blood vessel flow and vascular characteristics, such as narrowing or constriction, can impact the blood supply to the optic nerve head.

2.7 Feature Extraction and SVM:

In the context of identifying blood vessel patterns, researchers can extract relevant features from retinal images, such as vessel diameter, tortuosity, branching patterns, and flow characteristics. SVM can use these extracted features as input to learn the patterns associated with healthy retinal vasculature and those indicative of POAG-related changes.

2.8 SVM and Optic Nerve Head Damage:

As POAG progresses, increased intraocular pressure and vascular changes can lead to damage at the optic nerve head, causing irreversible vision loss. SVM's ability to recognize patterns in retinal blood vessels may help identify early indicators of vascular abnormalities that could lead to optic nerve damage.

2.9 Early Detection and POAG Prediction:

SVM's pattern recognition capabilities allow it to detect subtle changes in blood vessel patterns even before visible symptoms of POAG appear. Early detection of vascular changes can lead to timely intervention and management, potentially slowing down the progression of the disease.

2.10 Relationship to Glaucoma Development:

By analyzing retinal images and vascular patterns, SVM can help researchers identify associations between specific vascular changes and the development of POAG. Understanding the relationship between vascular alterations and glaucoma development can provide insights into the disease's underlying mechanisms and risk factors.

In summary, Support Vector Machine (SVM) is a powerful tool for pattern recognition, and its application in identifying blood vessel patterns in the retina can be relevant for understanding the development of primary open-angle glaucoma (POAG). By recognizing subtle changes in retinal blood vessels and their relationship to optic nerve head damage, SVM can potentially aid in early detection and prediction of POAG, leading to improved management and preservation of vision.

2.11 Dataset & Preprocessing

ORIGA Dataset: The ORIGA (Optic Nerve Head Image Database and Glaucoma) dataset containing 650 images/OCT scans overall, and out of which 500 images were considered for training set and 150 images were considered for testing. This entire data set includes the images of healthy, and patients affected with glaucoma of various age groups. Different features viz., Optic Nerve Head Morphology, Intraocular pressure, Age, Pollution Exposure have been considered in this proposed research. Initially, we have obtained a labeled dataset consisting of retinal images from glaucomatous and non-glaucomatous eyes. Each image has been associated with a corresponding class label (1 for glaucomatous, 0 for non-glaucomatous). Preprocessing has been done on the images to remove the noise, enhance the contrast levels, and normalized the pixel values. Each image is made up of pixels and each pixel values gives the intensity of the pixel ranging from 0 to 255 0 being white and 255 being black.

The features considered in the SVM Model are as follows. SVM classifier has been used to predict POAG based on the combined features extracted earlier [15][16]. We have trained the SVM model with the prepared dataset, where the features related to optic nerve head morphology, IOP, age, pollution exposure, and vascular reactivity serve as input features, and presence or absence of POAG serves as the two distinct classes.

We have extracted relevant features from the retinal images that describe the blood vessel patterns and vasoconstriction at the optic nerve head morphology. The features are vessel diameter, tortuosity, branching angles, and fractal dimension. In order to train and test the model, we have split the dataset into training and testing sets. The training set has been used to train the SVM model, while the testing set has been used to evaluate its performance. Confusion matrix has been considered for evaluating the model performance.

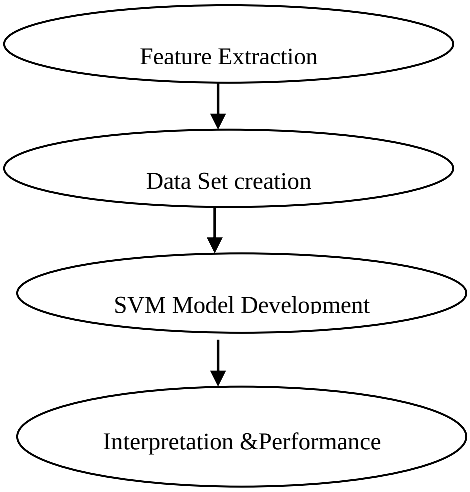

Fig. 1. Step by step approach (from top to bottom) for linear classification on ORIGA Glaucoma Data set to classify Glaucomatous and Non Glaucomatous Eyes

The SVM Hyper plane is on 5-dimensional vector space. Hyper Plane separates the data points on n-1 dimensional vector space . The general equation can be taken as $w^T x+b$ .where w, x are in n-dimensional space and b is bias. The five dimensional vector describes the quantity of distinct objects. From the clinical observation, In the absence of other abnormalities , fundus images exhibit glaucomatous related visual field defects and Glaucomatous Optic Neuropathy abnormalities . From the clinical based measurements, It is observed that, Intra Ocular Pressure(IOP) < 21mm Hg , Cup-Disc-Ratio >0.2 asymmetry and healthy eyes >=0.6mm[14][9] have been considered . Visual Field Defects made on sensitivity loss of P< 0.01, two or more points sensitivity loss of P< 0.05.ONH Morphology, combined data set images (Age related, Pollution Exposure) , IOP, vascular Reactivity(narrowing or blood vessel constriction) have been taken for consideration[8]. The images of glaucomatous and non glaucomatous eyes have been for training and testing purposes with the support of SVM. For assessing the performance of the model, Sensitivity, Specificity, Accuracy and Area under the Curve (AUC) have been considered. Python libraries like Pandas, SciPy have been used to implement the SVM model. The features are initially selected one by one from the data set pool. All features are grouped in a single set and the initial feature is randomly selected and the remaining features will be selected from the rest of the features available in the feature set. This process is repeated for the features on young aged glaucoma suspects and age related degeneration. The environment polluted demographic areas influencing the data to detect early stage Primary Open Angle Glaucoma has been described[17].

2.12 Implementation of SVM algorithm

The equation for the linear hyper plane can be written as

$$\mathbf{W^T x+b=0}$$

The vector w represents the normal vector to the hyper plane. The parameter b in the equation the distance of the hyperplane from the origin in the direction of the vector w. The distance between the hyperplane and the datapoint x_i can be computed as

$$\mathbf{d_i = (W^T x+b) / \|w\|}$$

where $\|w\|$ represents the Euclidean norm of the weight vector W. For linear SVM classifier, we have

$$\mathbf{y^\wedge = \{ 1 : W^T x+b >=0 \quad 0: W^T x+b<0 \}}$$

In general, for Hard margin linear classifier, we have

$$\underset{W,b}{\text{Minimize}}\ \tfrac{1}{2} W^T W = \text{minimize } \tfrac{1}{2} \|w\|^2$$

subject to the constraints $y_i (w^T x_i +b)>=1$ for i=1,2,3,…..m

The label for the i^{th} training instance is given by the symbol t_i, and $t_i=-1$ for negative occurrences when $y_i =0$ and $t_i=1$ positive instances when $y_i=1$ respectively. The decision boundary should satisfy the condition: $t_i(w^T x_i+b)>=1$.

For softmargin linear classifier, we have

$$\text{Minimize } \tfrac{1}{2} w^T w + C \sum_{i=1}^{m} \xi_i$$

subject to $y_i (w^T x_i +b)>=1-\xi_i$ and $\xi_i >=0$ for i=1,2,3,….,m.

For softmargin linear classifier, we have

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subject to $y_i (w^T x_i +b)>=1-\xi_i$ and $\xi_i >=0$ for i=1,2,3,….,m.

The dual problem of the optimization problem, that needs identifying the Lagrange multipliers related to support vectors may be utilized to solve the SVM. The optimal Lagrange multipliers α(i) that maximizes the dual objective function

$$\text{Maximize: } 1/2 \sum_{i \rightarrow m} \sum_{j \rightarrow m} \alpha_i \alpha_j t_i t_j K(x_i,x_j) - \sum_{i \rightarrow m} \alpha_i$$

where α_i is the Lagrange multiplier associated with ith training example. $K(x_i,x_j)$ is the kernel function that computes the similarity between two samples x_i and x_j.

This kernel function allows the SVM to handle non-linear classification problems by mapping the examples intoa higher dimensional feature space. The SVM decision boundary can be described interms of these optimal Lagrange multipliers and the support vectors. The training examples that have i>0 are the support vectors while the decision boundary is supplied by

$$W=\sum \alpha_i t_i K(x_i,x) + b \text{ and}$$

$$t_i(w^T x_i - b) = 1 \Leftrightarrow b = w^T x_i - t_i$$

3. Results and Discussion

The results generated by the SVM model have been given below. The model evaluation parameters Sensitivity, Specificity, Area Under the Curve (AUC) and Accuracy of the model have been computed taking into consideration of group of features of the images. Different levels of the Glaucotomous disease have been taken in generating the results. The levels are Normal, Early stage, Moderated stage and Advanced stage. The results with respect to Normal eye versus early stage of Glaucoma, Normal eye versus Moderated stage and Normal eye versus Advanced stage have been computed and depicted in the following tables.

Features	Sensitivity	Specificity	Accuracy	AUC
Optic Nerve Head Morphology	0.91	0.18	0.60	0.58
Intra Ocular Pressure	0.79	0.71	0.75	0.78
Age	0.73	0.70	0.72	0.77
Pollution Exposure	0.76	0.72	0.74	0.77
Vascular Reactivity	0.74	0.47	0.72	0.67

Table-1: Results of Normal Eye versus Early stage of Glaucoma

In table-1 above, Optical Nerve Head has produced higher sensitivity compared to other features IoP (Intraocular Pressure), Age of an individual, Air pollution exposure (PE) and vascular reactivity (VR). When it comes to specificity, PE has high impact compared to other features Optic Nerve Head Morphology (ONHM), IoP, Age and VR. The model has produced high accuracy with regard to IoP. Similarly, the features IoP and PE have a lot of impact with respect to area under the curve (AUC) indicating that, PE has high impact on the patients suffering from Glaucoma during early stages of the disease.

Features	Sensitivity	Specificity	Accuracy	AUC
Optic Nerve Head Morphology	0.04	1	0.77	0.66
Intraocular Pressure	0.72	0.96	0.91	0.89
Age	0.60	0.97	0.89	0.86
Pollution exposure	0.78	0.97	0.93	0.89
Vascular Reactivity	0.45	0.97	0.85	0.79

Table-2: Results of the Normal Eye versus Moderated stage of Glaucoma

In table-2, The model has generated high PE compared to other features indicating that the PE has high impact on the patients affected with moderated Glaucoma. Similarly, Optic Nerve Head has high impact compared with other features indicating that, ONH has a high impact on the Glaucoma patients in the moderated stage. The accuracy of the model is high with regard to PE indicating the impact of pollution on the Glaucoma patients in the moderated stage of the disease. Interestingly, The AUC with regard to IoP and PE are high indicating the fact that both the features have very high impact on the glaucoma patients with moderated stage.

Features	Sensitivity	Specificity	Accuracy	AUC
Optic Nerve Head Morphology	0.72	0.72	0.72	0.67
Intraocular Pressure	0.94	0.94	0.94	0.92
Age	0.92	0.92	0.92	0.91
Pollution Exposure	0.95	0.95	0.95	0.95
Vascular Reactivity	0.91	0.91	0.91	0.87

Table-3: Results of the Normal Eye Versus Advanced Stage

In table-3, the sensitivity of the SVM model is very high with regard to IoP, PE and to certain extent VR on the patients suffering from Glaucoma with advanced stage. The IoP and PE are also very high with regard to specificity indicating that patients suffering from Glaucoma in advanced stage have high impact on the presence of the pollution in the air. The model has produced high accuracy values with regard to IoP, PE indicating that, the patients suffering from Glaucoma in advanced stage have high risk of pollution. Interestingly, the age of the patient has an impact on Glaucoma disease. Finally, IoP has shown high impact compared to PE on the Glaucoma patients suffering from advanced stage.

4. Conclusion

This study is to predict POAG integrated with age-related degeneration and environmental pollution which is responsible for the vasoconstriction at ONH . Diverse age groups have been considered by using clinical records, imaging data, and environmental parameters. In this model, SVM based feature extraction establishes to distinguish glaucomatous and non glaucomatous eyes[13][18]. With the addition of more training data containing images and also adding more features from OCD Segmentation, this study can further develop a robust SVM- based prediction model for POAG, facilitating risk assessment and early intervention with more accuracy.

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