THE PREDICTION OF GLAUCOMA FROM OCULAR BIOMETRIC DATA*

Part 1
An Application of Multiple Regression Analysis

A. Tomlinson† and
C. N. French‡ University of
Manchester Institute of
Science and Technology
Manchester, England

ABSTRACT

Two sets of multiple regression equations (prediction systems) were derived from the analysis of ocular biometric data obtained from glaucoma patients (16 open angle; 16 angle-closure), and 75 normal subjects. Discriminant scores were established for both sets of equations which minimised the number of false negatives. One set, the 'Glaucoma Equations' was applied to the data to segregate the glaucoma from the normal subjects. The other prediction system, the 'Classification Equations,' was then applied to the group defined as glaucomatous to discriminate between patients in the angle-closure and open angle categories. The performance of these equations, obtained by comparing the predicted and actual classifications for this sample, was such that between 9 and 12% of false positives and 0 and 3% false negatives were found on the 'Glaucoma Equations' and between 6 and 12% of false positives with no false negatives on the 'Classification Equations.'

The importance of ocular dimensions in the aetiology of angle closure glaucoma is well established. The axial chamber depth is shallow compared with the normal and has long been considered a feature of the condition.[1-6] The shallow anterior chamber in angle-closure glaucoma has been attributed to the presence of a large lens in a small eye;[1] and it is true that the thickness of the crystalline lens is greater in the eye with this form of glaucoma than in the normal and that the length of the eyeball is less.[5-7] Lowe[7] has suggested that the shallow anterior chamber is principally due to 'incoordinations' of structure between the lens and eyeball, the 'thick' lens being sited too far forward within the globe.

The corneal dimensions of radius[8-10] and diameter[5, 6, 9] have been found to be smaller in the eye with angle-closure glaucoma than in the normal. The effect of corneal height on the axial depth of the anterior chamber has been

* Submitted February 24, 1975 for publication in the December, 1975 issue of the AMERICAN JOURNAL Of OPTOMETRY AND PHYSIOLOGICAL OPTICS.

t Optometrist, Ph.D., Member of Faculty. Present address: School of Optometry, University of California, Berkeley, California 94720.

‡ Psychologist, M.A., Member of Faculty

considered by Delmarcelle, Collignon-Brach and Luckyx-Bacus, [11] and by Storey and Phillips; [5] the anterior chamber is found to be shallower in eyes with small corneal heights. Delmarcelle, Collignon-Brach and Luckyx-Bacus[12] have shown that corneal height is a function of cornea] radius and diameter. Storey and Phillips[5] and Tomlinson and Leighton[6] report that the corneal height is less in eyes with angle-closure glaucoma than in the normal. It is not surprising from the foregoing that the condition occurs most frequently, but not exclusively, in eyes which are hypermetropic.[13,14] It has been shown that hypermetropia is associated with a shallow anterior chamber[2*15] and that the higher degrees of hypermetropia are found most frequently in small eyes with relatively flat corneas.[15]

The influence of ocular dimensions on the aetiology of open angle or simple glaucoma is not as great as in angle-closure glaucoma. There is some evidence however to suggest that the myopic eye may be particularly sensitive to rises in intra-ocular pressure; the incidence of myopia in patients with simple glaucoma is relatively high.[16,,18] Tornquist and Brode'n[19] and Storey and Phillips[5] have observed that eyes with this form of glaucoma have significantly shallower anterior chambers than the normal and these latter co-workers have found that the thickness of crystalline lens is significantly greater than normal.

The roles of ocular dimensions in the heredity of angle-closure glaucoma has been discussed by Tornquist, [20] Miller, [21] Lowe[22] and Tomlinson and Leighton; [6] and in the heredity of simple glaucoma by Tomlinson and Leighton[23] — both dominant and multi-factorial modes of transmission have been suggested.

This review of the characteristic biometric features of eyes with angle-closure and simple glaucoma leads us to consider if it is possible from the measurement of the ocular dimensions of any eye to *predict,* on this biometric data alone, if that eye has, or is likely to, develop either condition. A method by which such predictions may be made is that of regression analysis. Such a technique has been applied previously to the diagnosis of primary carcinoma of the lung or bronchus[24] and to the prediction of coronary artery disease.[25] The use of multiple linear regression model in this and other investigations allows the testing of hypotheses concerning the contributions of relevant variables, in this case ocular dimensions, to the prediction of a criterion, namely the presence or absence of the condition. The analysis considered below has been based on an intercorrelation matrix of 14 predictor (independent) variables and a binary criterion of the presence or absence of glaucoma at the time the data was collected. The correlation matrix was obtained from the raw scores obtained from the measured values of 11 ocular dimensions to which were added three other variables i.e., age, sex and the laterality of the eye considered, which were given values of 1 for male and left eye and 2 for female and right eye. The presence of the condition was confirmed by specialist medical opinion applying the diagnostic criteria of raised intra-ocular pressure, partial or full closure of the angle on gonioscopic examination, enlarged areas of cupping at the optic disc and characteristic field changes.

MATERIAL

Subjects:

The data analysed in this study was obtained from 16 patients with angle-closure glaucoma, and 16 patients with open-angle (simple) glaucoma who attended the University Unit of the Manchester Royal Eye Hospital.

The other 75 subjects were 'normal' in that they had no demonstrable ocular pathology or family history of glaucoma. This latter group of subjects consisted of University Staff, Students and Patients attending for measurements of refraction.

METHOD

Ocular Biometry:

The eleven recorded ocular dimensions with their methods of measurement were:

i) CR– Mean corneal radius i.e. $\frac{(\text{horizontal} + \text{vertical})}{2}$ measured by Zeiss Keratometry,

ii) CD– Horizontal corneal diameter from a colour photograph of the anterior surface of the eye,

iii) CT– Corneal thickness by the Type I attachment for the Haag-Streit 900 slit lamp,

iv) CH— Corneal height calculated from the formula,

$$\text{height} = \text{corneal radius} - \sqrt{(\text{corneal radius})^2 - \frac{(\text{corneal dia.})^2}{4}}$$

(see Delmarcelle et al, 1969),

v) ACD— Axial depth of the anterior chamber measured with the Type II attachment for the Haag-Streit slit lamp.

vi) LTH— Thickness of crystalline lens

vii) VL— Length of vitreous body

} from an anterio-posterior axis trace of the eye obtained by A-Scan ultrasonography.

viii) AL— Axial length of the eyeball — found from the addition of v) vi) and vii).

ix) RLP— Relative lens position calculated from the formula,

$$\frac{\text{ant. chamber depth} + \frac{1}{2}\text{ lens thick.}}{\text{axial length}}$$

(see Lowe 1970).

x) IOP— The highest intra-ocular tension recorded at any time with the applanation tonometer attached to the Haag-Streit slit lamp.

xi) BSR— Best sphere refraction i.e., sphere + ½ power of the cylinder, obtained by objective and subjective refraction.

To these dimensions were added the age and sex of the subject, and the laterality of the eye measured, to form the fourteen independent variables considered.

STATISTICAL METHOD:

The aim of multiple regression analysis is to obtain an equation which from a linear combination of independent variables produces the best prediction of the dependent variable. The equation can be written:

$$D = b_1I_1 + b_2I_2 + b_3I_3 \ldots . + b_nI_n + c + r$$

where D is the dependent variable; there are n independent variables (I_1 to I_n) each with its associated regression coefficient (b_1 to b_n); c is a constant; and r is the residual or discrepancy between the calculated and observed dependent variables. If the regression equation were perfect then the residual would be zero for all cases in the sample being studied, but in practice it varies. Its mean, however, will be zero and the regression analysis will result in a set of regression coefficients which give its standard deviation a minimum value for the specified set of independent variables.

The regression equation can be expressed in two ways. The independent variables can be measured on their raw, untransformed scales or alternatively the scales can be standardised so that their mean is zero and their standard deviations unity. This latter technique has the advantage that the regression coefficients then provide a direct indication of the importance of the associated independent variable in the equation. The constant, c is zero for this form. The standardised form of the equations, although not published here, were calculated and the normalized regression coefficient for each variable taken as an indication of its importance in the selection of variables on the basis of contribution (see later).

There may be a large group of independent variables which are candidates for a regression equation. It does not follow, however, that it is useful to include all of these. It may be possible to achieve almost as efficient predictions of the dependent variable from a small sample of the variables. Decisions on whether or not variables should be included may be made on several bases. Some variables are very easily measured and the cost of inclusion is very little in which case there seems little reason to exclude them. On the other hand a variable may and considerably to the predictive power of the equation, but at the same time be difficult to measure. Decisions then will be based on practical as well as statistical grounds.

The statistical basis for the selection of a new variable is dependent on the amount of previously unexplained variance which the new variable contributes by its inclusion. This variance is the product of two values: the square of the normalized regression coefficient which that variable would be given if incorporated in the equation, and the tolerance which indicates the degree to which the new variable represents a new dimension in the equation. If the tolerance is small then the new variable merely represents a linear combination of those variables already in the equation and even if it is assigned a high regression coefficient it will not add substantially to the explained variance.

Variables may be added to the regression equations at one's discretion -in a sequence which makes sense from practical, theoretical,

or statistical grounds. Alternatively the step at which a new variable is brought in can be left entirely to statistical considerations by the use of the stepwise multiple regression procedure. This method selects from among the variables available the optimum one which at the next step will add most to the already explained variance. It uses the information given by the tolerance and potential regression coefficient. It will not include new variables if their tolerance is below a specified minimum level. The values for the minimal F level ($p < 0.01$) and the tolerance level for the inclusion of variables in stepwise mode (0.001) were the default values provided within the multiple-regression subprogramme from the SPSS package[26] which was used throughout for the calculations in this study.

Two sets of regression equations or prediction systems were obtained, the first from analysis of the data obtained for the angle-closure glaucoma, open-angle glaucoma and normal subjects; the second from an analysis of the data for the angle-closure and simple glaucoma patients alone. These sets of equations will be referred to respectively as the 'Glaucoma Equations' and the 'Classification Equations,' and may be seen in Tables 1 and II. Both full prediction systems containing all fourteen variables and reduced prediction systems con-

TABLE I: The table shows regression equations for full and reduced prediction systems with groups of variables chosen on the bases of contribution and contribution combined with ease of measurement. The equations show the loadings for the raw data.

'Glaucoma Equations'

A. Groupings on the Basis of Contribution.

a) All Variables Prediction System ($R^2 = 0.728$)

$Y = +6.044CR + 0.103CD + 0.827CT - 0.721CH - 0.500ACD - 0.054LTH - 0.034VL + 0.046AL + 3.264RLP + 0.0401OP - 0.047BSR - 0.001\ AGE + 0.103\ SEX + 0.004\ EYE - 0.705.$

b) Reduced Prediction System ($R^2 = 0.726$) — Variables CR,CT,AGE and EYE i.e., minor contributors omitted.

$Y = 0.124CD - 0.735CH - 0.509ACD + 0.015LTH - 0.033VL + 0.052AL + 2.746RLP + 0.0401OP - 0.044BSR + 0.103\ SEX - 0.009.$

c) Reduced Prediction System ($R^2 = 0.717$) — Variables CR,CD,CT,LTH,VL, AL,RLP,AGE,SEX and EYE i.e. lesser contributors omitted.

$Y = -0.507CH - 0.462ACD + 0.0401OP - 0.043BSR + 2.257.$

d) Reduced Prediction System ($R^2 = 0.675$) — Variables CR,CD,CT,CH,LTH, VL,AL,RLP,BSR,AGE,SEX and EYE omitted i.e. only principal contributors included.

$Y = -0.414ACD + 0.0421OP + 0.832.$

e) Reduced Prediction System ($R^2 = 0.611$) All variables except IOP excluded.

$Y = 0.0511OP - 0.632.$

B. Groupings on the Basis of Contribution and Ease of Measurement.

a) Reduced Prediction System ($R^2 = 0.723$) — Variables LTH,VL,AL and RLP i.e. smaller contributors and difficult measures omitted.

$Y = 0.003CR + 0.116CD + 0.600CT - 0.664CH - 0.460ACD + 0.0401OP - 0.043BSR + 0.001\ AGE + 0.087\ SEX - 0.015\ EYE + 0.815.$

b) Reduced Prediction System ($R^2 = 0.710$) — Variables CD,CH,LTH,VL,AL, and RLP i.e. lesser contributors and difficult measures excluded.

$Y = 0.117CR + 0.598CT - 0.527ACD + 0.0401OP - 0.047BSR + 0.001\ AGE + 0.067\ SEX - 0.016\ EYE - 0.135.$

c) Reduced Prediction System ($R^2 = 0.705$) — Variables CR,CD,CT,CH,LTH,VL,AL, RLP,AGE, SEX and EYE omitted i.e. only easiest measures with some contribution included.

$Y = 0.551ACD + 0.0401OP - 0.048BSR + 1.341.$

taining variables selected on the bases of contribution and contribution combined with ease of measurement are shown. The intention was that any subject for whom some or all the variables have been found may be defined on the basis of the score obtained in the 'Glaucoma Equations' as a glaucoma patient or as a normal subject. If the patient was placed *within* the glaucoma group, by the application of the appropriate 'Classification Equation* it was hoped that the patient's condition may then be classified as, angle-closure or open-angle glaucoma.

To assess the values of the prediction systems described above a weighted raw score for each case was computed. The scores for all the groups of subjects were ranked and a cut-off or discriminant score found, which in the case of the 'Glaucoma Equations' optimised the number of glaucoma subjects correctly defined as distinct from the normal group, and in the case of the 'Classification Equations' when applied to the glaucoma subjects most clearly segregated the open-angle from the angle-closure subjects (see Tables III and IV).

RESULTS:

The general efficiency of each prediction system or regression equation may be assessed by considering the amount (or percentage) of the total criterion variance which is accounted for in each equation; this may be found from the squared multiple-correlation coefficients (R^2). The criterion for the prediction systems of Table I is whether the subject has glaucoma (of either type) or not. The full prediction equation (Aa) containing all 14 variables accounts for 72.8% (R2 = 0.728) of the criterion variance, a fair representation of this variance,

TABLE II: The table shows regression equations for full and reduced prediction systems with groups of variables chosen on the bases of contribution and contribution combined with ease of measurement. The equations show the loadings for the raw data.

'Classification Equations'

A. Groupings on the Basis of Contribution.

a) All Variables Prediction System ($R^2 = 0.728$)

$Y = 0.539CR + 0.147CD + 2.248CT - 0.208CH - 1.224ACD - 0.443LTH - 0.529VL + 0.323AL + 0.680RLP + 0.0011OP - 0.085BSR - 0.010AGE + 0.022SEX + 0.035EYE + 1.553.$

b) Reduced Prediction System ($R^2 = 0.784$) – Variables RLP,CH,SEX,EYE and IOP i.e. minor contributors omitted.

$Y = 0.555CR + 0.069CD + 1.982CT - 1.152ACD - 0.365LTH - 0.464VL + 0.250AL - 0.086BSR - 0.010AGE + 2.323.$

c) Reduced Prediction System ($R^2 = 0.711$) – Variables CR,CD,CT,RLP,CH AGE, SEX, EYE and IOP omitted i.e. lesser contributors.

$Y = 1.039ACD - 0.339LTH - 0.161VL + 0.080AL - 0.057BSR + 6.645.$

d) Reduced Prediction System ($R^2 = 0.601$) all variables except ACD excluded.

$Y = -0.720ACD + 3.448.$

B. Groupings on the Basis of Contribution and Ease of Measurement

a) Reduced Prediction System ($R^2 = 0.778$) – Variables CD,LTH,RLP and CH i.e. smaller contributors and difficult measures omitted.

$Y = 0.516CR + 2.119CT - 0.799ACD - 0.187VL - 0.016AL - 0.082BSR + 0.0011OP - 0.013AGE + 0.012SEX + 0.017EYE + 2.519.$

b) Reduced Prediction System ($R^2 = 0.691$) – Variables CD,LTH,VL,AL,RLP,CH, SEX, EYE and IOP i.e. lesser contributors and difficult measures omitted.

$Y = 0.050CR + 0.710CT - 0.927ACD - 0.037BSR - 0.010AGE + 3.914.$

c) Reduced Prediction System ($R^2 = 0.656$) – Variables CR,CD,CT,LTH,VL,AL, RLP,CH,AGE,SEX,EYE and IOP i.e. only easiest measures with some contribution included.

$Y = -0.832ACD - 0.041BSR + 3.771.$

which suggests a fairly efficient prediction system. When the four smallest contribution variables, found from the variable loadings in the alternative standardised form of the equations (but not included here) are excluded from the equation (Ab), very little loss of predictive ability occurs (R^2 = 0.726). Indeed with the exclusion of ten variables from the original full prediction system in equation Ac, only 1.1% accountability for the criterion variance is lost. With the single variable prediction system of equation Ae, 61.1% of the criterion variance is still accounted for. Some loss of predictive efficiency must occur when variables are excluded in an attempt to simplify these equations but it is encouraging that the loss is so small.

In the second group of equations in Table I, variables are excluded on the basis of contribution combined with ease of measure. The exclusion of variables requiring ultrasonographic measurements and surface photography of the eye, equation Bb, gives an R^2 value of 0.710; while the result of taking the three simplest measures only, equation Bc is to reduce the amount of the criterion variance accounted for to 70.5%.

The criterion for the 'Classification Equations' of Table M is the presence of angle-closure glaucoma or simple glaucoma. The equation containing all 14 variables accounts for 78.5% of the total criterion variance (Aa), again a fairly efficient prediction system. Little efficiency is lost on removal on the basis of small contribution, of five variables from equation Ab. (R^2 = 0.784). The removal of a further four variables in equation Ac reduces the criterion variance accounted for by a further 7.3%. The single variable equation Ad this time accounts for 60.1% of the variance. The attempt to obtain a reduced prediction system with easily measurable variables also results in some loss of efficiency. Compared to the full prediction system 9.4% loss of the criterion variance is accounted for by the equation Bb, requiring no ultrasonographic or surface photography- measurements, and the equation Be utilizing axial chamber depth and refractive findings only, accounts for 65.6% of the variance.

TABLE III: The table shows the effectiveness of the *Glaucoma Equations' when applied to the present data with the discriminant score for glaucoma as indicated.

Regression Equation (see Table I)	Value of R^2	Variables in Equation	Discriminant Score	False Positives Number (%)	False Negatives Number (%)
Aa	0.728	14 – All variables	⩾0.41	7 (9)	1 (3)
Ab	0.726	10 – CD,CH,ACD,LTH, VL,AL,RLP,IOP, BSR and SEX.	⩾0.37	8 (11)	1 (3)
Ac	0.717	4 – CH,ACD,IOP, and BSR.	⩾0.39	9 (12)	1 (3)
Ad	0.675	2 – ACD and IOP.	⩾0.41	8 (11)	1 (3)
Ae	0.611	1 – IOP.	⩾0.30	8 (11)	1 (3)
Ba	0.723	10 – CR,CD,CT,CH, ACD,IOP,BSR, AGE,SEX and EYE.	⩾0.40	7 (9)	0 (0)
Bb	0.710	8 – CR,CT,ACD,IOP, BSR,AGE,SEX and EYE.	⩾0.40	7 (9)	0 (0)
Bc	0.705	3 – ACD,IOP and BSR.	⩾0.42	7 (9)	1 (3)

False positive, is the-classification of a normal subject incorrectly in the glaucoma category.
False negative, is the classification of a glaucoma subject incorrectly as a normal.

The performance of the various prediction systems in defining and classifying glaucoma for the subjects of this study are shown in Tables III and IV. The discriminant scores shown in these tables were chosen to give the largest number of cases in which the predicted classification matches the actual classification with the number of false negatives kept to a minimum. In the preliminary segregation of subjects into glaucomatous and normal categories (Table III), the 'error' in classification varies between 9 and 12% for false positives and 0 and 3% for false negatives; expressed as a percentage of the whole sample these represent 'overall' errors of between 7 and 15%. As would be anticipated from the R^2 value for each equation, the number of misclassifications generally increases with a reduction in the number of variables in the prediction equation; however, the effect of a loss of accountability for variance of 11.7% is to produce only two further false positives and one false negative for this sample. For the subsequent classification of the glaucoma subjects into angle-closure and open-angle groups (Table IV), an efficiency of only 65.6%, as in the case of equation Ad, is sufficient to correctly classify all but two subjects. Indicating that we have some redundant efficiency in our larger equations for the data of this study.

DISCUSSION:

The choice of multiple linear regression analysis for the derivations of a method of prediction of glaucoma from biometric data was chosen because of its suitability to this type of problem in medical diagnosis.[24, 25] The use of an iterative technique ensured that the computation had the best chance of continuing to a solution. Alternative methods such as factor analysis[27] are being applied to the data but the derivation, by this technique, of several factors composed of all 14 variables makes the clinical application of the results more complex.

Two methods of multiple regression analysis were employed in this study. In one, the variables were chosen on the basis of contribution i.e., by their loading on the standardised form of the regression equation, and by contribution combined with ease of measurement. In a second, a stepwise analysis was used in which a new variable was included in the analysis on the basis that it was the one which at the next step would add most to the accountability of variance. This latter technique proved inferior to

TABLE IV: The table shows the effectiveness of the 'Classification Equations' when applied to the data of subjects defined as glaucomatous by the 'Glaucoma Equation' Aa, with the discriminant score for angle-closure glaucoma as indicated.

Regression Equation (see Table II)	Value of R^2	Variables in Equation	Discriminant Score	False Positives Number (%)	False Negatives Number (%)
Aa	0.785	14 – All variables	⩾1.40	1 (6)	0 (0)
Ab	0.784	9 – CR,CD,CT,ACD, LTH,VL,AL,BSR, AGE	⩾1.41	1 (6)	0 (0)
Ac	0.711	5 – ACD,LTH,VL,AL, BSR	⩾1.49	1 (6)	0 (0)
Ad	0.601	1 – ACD	⩾1.54	1 (6)	0 (0)
Ba	0.778	10 – CR,CT,ACD,VL, AL,BSR,IOP, AGE,SEX,EYE	⩾1.39	1 (6)	0 (0)
Bb	0.691	5 – CR,CT,ACD,BSR, AGE	⩾1.52	2 (12)	0 (0)
Bc	0.656	2 – ACD,BSR	⩾1.47	2 (12)	0 (0)

False positive, is the incorrect classification of an actual open angle glaucoma subject, as an angle-closure case.
False negative, is the classification of an actual angle-closure glaucoma subject incorrectly as a case of simple glaucoma.

the former as it failed to select variables in the order which gave maximum clinical utility.

The choice of variables to be included in the analysis was made on the reported evidence of characteristic differences for these variables between patients with one or both forms of glaucoma and the normal. It is possible that other factors such as the equatorial diameters of lens and eyeball, the volume of the anterior chamber or globe may be important but in the absence of published evidence and because of the difficulties of measurement, they were excluded. Both full and reduced prediction systems were derived for the variables considered. The advantage of the 14 variable regression equation was that it gave the greatest prediction ability, whilst the derivation of smaller equations with fewer variables enabled predictions to be made with fewer and often more readily available techniques of measurement. This is an important consideration if the derived equations are to have any clinical application. An added advantage of having several prediction equations available, based on different combinations of variables, is that when applied to other samples one or more equations may still be used if some data is missing.

Another use to which multiple regression analysis may be put, is the evaluation of the importance of groups of variables in prediction.[25] For example it is possible to derive a regression equation without any corneal variables i.e. corneal radius, diameter, thickness and height, by comparing the R^2 value for this equation with the R^2 value for the full prediction system. The difference in these values indicates the amount of criterion variance attributable to the corneal factors. This was not undertaken in this study as our main concern in deriving reduced prediction systems was to obtain the most efficient or useful possible with individual variables, irrespective of the group to which the variables belonged.

In this study the highest recorded intraocular pressure was considered. This value obtained before any surgical or medical treatment had been undertaken or in some cases during phasing or provocation tests may not be the value recorded if a subject is seen after treatment, or on only one occasion. We nevertheless felt justified in considering this value as it did represent one definite measurement of the variable (instead of one of a series of similar lower measurements taken following treatment), and as most glaucoma Suspects' do have one relatively high recorded tension which is often the reason for their referral. It is possible, however, that some bias may have been introduced into the results as a consequence of this decision. The normal subjects did not in all cases have their ocular tensions taken on the same number of occasions or under the same conditions (phasing, provocation) as the glaucoma groups.

In considering the results of this study it is perhaps not surprising that the single variable which most effectively discriminates between glaucoma and the normal is intra-ocular pressure (Table I) and between open-angle and angle-closure glaucoma is axial chamber depth (Table II). The importance of these dimensions is thus underlined.

The ability to predict with these regression equations the presence and type of glaucoma for our sample, is much superior to the previously reported efficiency of such procedures as provocative tests[2] &>[29] and tonography[30] in other studies. The discriminant values (Tables III and IV) for each equation were chosen to minimise the number of false negatives obtained i.e., the incorrect classification of a glaucomatous patient as normal or an angle-closure glaucoma case as simple glaucoma. It is an important pre-requisite from a clinical standpoint of this form of prediction system, that as few *affected individuals as possible are incorrectly classified and left untreated. The small number of false negatives is often at the cost of a larger number of false positives, i.e. normals classified as glaucomatous, or simple glaucoma described as angle closure. Although the latter is undesirable from an economic and humanitarian standpoint if this leads to these patients being treated unnecessarily, it is preferable to the alternative.

The efficiency of any prediction 'system based on regression analysis is greatest when applied to the data from which it is derived. This is particularly so when interpreting the results of such analysis when a binary criterion is used.[25] The F tests of significance are quite robust when applied in general circumstances, [31] but the ultimate test of the prediction ability is the accuracy of classification when the equations are applied to other samples. The prediction of glaucoma from ocular

biometric data will require further testing on other and larger groups of data before any clinical acceptance can be forthcoming of this technique.

ACKNOWLEDGMENT

We wish to thank Professor C. I. Phillips (former Head of the University Department of Ophthalmology, Manchester Royal Eye Hospital), for permission to obtain from his patients the data for this study.

REFERENCES

1. Smith, Priestley (1883). On Growth of the Crystalline Lens. Trans. Ophthal. Soc. U.K. 3,79-99.
2. Rosengren, B. (1950). Studies in the Depth of the Anterior Chamber of the Eye in Primary Glaucoma. Arch. Ophthal. 44, 523-538.
3. Tornquist, R. (1956). Chamber Depth in Primary Acute Glaucoma. Brit. J. Ophthal.40,421-429.
4. Lowe, R. F. (1968). Time-amplitude Ultrasonography for Ocular Biometry. Amer. J. Ophthal. 66, 913-918.
5. Storey, J. K. and Phillips, C. I. (1971). Ocular Dimensions in Angle Closure Glaucoma. Brit. J. Phys. Opt. 26, 228-242.
6. Tomlinson, A. and Leigh ton, D. A. (1973). Ocular Dimensions in the Heredity of Angle Closure Glaucoma. Brit. J. Ophthal. 57,475-486. -
7. Lowe, R. F. (1970). Aetiology of the Anatomical Basis for Primary Angle-Closure Glaucoma. Brit. J. Ophthal. 54, 161-169.
8. Tornquist, R. (1957). Corneal Radius in Primary Acute Glaucoma. Brit. J. Ophthal. 41,421-424.
9. Grietens, J. and Weekers, R. (1962). Etude des Dimensions de la Anterieure de 1'Oeil humaine III. Ophthalmologica 143, 409-422.
10. Lowe, R. F. (1969). Corneal Radius and Ocular Correlations: In Normal Eyes and Eyes with Primary Angle-Closure Glaucoma. Amer. J. Ophthal. 67, 864-872.
11. Delmarcelle, Y., Collignon-Brach, J. and Luckyx-Bacus, J. (1970). Role de la Cornee et du Cristallin sur la Biométric de la Chambre Anterieure du Subjet Normal. Arch. Ophthal. (Paris) 30, 291-300.
12. Delmarcelle, Y., Collignon-Brach, J. and Luckyx-Bacus, J. (1969). La Profondeur de la Chambre Anterieure de 1'Oeil Normal et ses Facteurs Constituants. Bull. Soc. Beige d'Ophthal. 152,447-453.
13. Sugar, H. S. (1941). The Mechanical Factors in the Etiology of Acute Glaucoma. Amer. J. Ophthal. 24, 851-873.
14. Lowe, R. F. (1961). Angle Closure Glaucoma: Acute and Subacute Attacks: Clinical Types. Trans. Ophthal. Soc. Aust. 21, 65-74.
15. Sorsby, A., Benjamin, B., Davey, J. B., Sheridan, M., and Tanner, J. M. (1957). 'Emmetropia and Its Aberrations/ Spec. Rep. Ser. Med. Res. Counc. No. 293, H.M.S.O. London.
16. Perkins, E. S. and Jay, B. S. (1960). Pigmentary Glaucoma. Trans. Ophthal. Soc. U.K. 80, 153-167.
17. Weekers, R., Lavergne, G. and Prijot, E. (1958). La Correction des Mesures Tonometriques chez les Sujets a Rigidite Oculaire Basse on Haute. Ann. Oculist (Paris) 191, 26-31.
18. Diaz-Dominguez, D. (1966). La Miopia Progresiva Forma Especial de Glaucoma. Arch. port. Oftal. 18, 13-22.
19. Tornquist, R. and Broden, G. (1958). Chamber Depth in Simple Glaucoma. Acta. Ophthal. Kbh. 36, 309-323.
20. Tornquist, R. (1953). Shallow Anterior Chamber in Acute Glaucoma. Acta. Ophthal. Kbh. Supp. 39.
21. Miller, S. J. H. (1970). Genetics of Closed-Angle Glaucoma. J. Med. Gen. 7, 250-252.
22. Lowe, R. F. (L972). Primary Angle Closure Glaucoma, Inheritance and Environment. Brit. J. Ophthal. 56, 13-20.
23. Tomlinson, A. and Leighton, D. A. (1974). Ocular Dimensions in the Heredity of Open Angle Glaucoma. Brit. J. Ophthal. 58, 68-74.
24. Hollingsworth, T. H. (1959). Using an Electronic Computer in a Problem of Medical Diagnosis. Statist. Soc. A. 122, 221-231.
25. Ward, H. and Hook, M. (1962). Use of Regression Analysis and Electronic Computers in the Prediction of Coronary Artery Disease. Behav. Sc. 7, 120-126.
26. Nie, N. H., Bent, D. H., and Hull, C. H. (1970). Statistical Package for the Social

Sciences p. 174. McGraw-Hill, New York.
27. Overall, J. E. and Williams, C. M. (1961). Models for Medical Diagnosis: Factor Analysis. Med. Doc. 5, 51-56.
28. Duke-Elder, W. S. (1969a). System of Ophthalmology Volume XI, p. 498. Kimpton, London.
29. Duke-Elder, W. S. (1969b). System of Ophthalmology Volume XI, p. 498. Kimpton, London.
30. Gloster, J. (1966). 4Tonometry and Tonography.' Churchill, London.
31. Box, G. E/P. and Anderson, S. H. (1955). Permutation theory in the derivation of robust criteria and the study of departures from assumption. J. R. Statist. Soc. B. 17, 1-26.

AUTHORS' ADDRESS:
University of Manchester Institute of Science & Technology P.O. Box 88 Manchester M60 IQD, England