

Identifying Best Machine Learning Model For Prediction Of Cataract Status Using Network Information Criterion

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ABSTRACT

Cataract is an eye condition that makes people very difficult to see things clearly. Previous studies reviewed on Machine Learning (ML) used cross-validation, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) to select best Machine Learning (ML) model for prediction of Cataract but the use of Network Information Criterion (NIC) remain a challenge. The data used was from on-going research by the corresponding author on eye diseases and it was collected through personal interview at National Eye Centre (NEC) Kaduna from 25th Nov. to 19th Dec. 2024 after ethical approval was given on 21st October, 2024. The study computed the NIC values of Support Vector Machine (SVM), Decision Tree (DT), K-Nearest Neighbour (K-NN), Naïve Bayes (NB) and Multilayer Perceptron (MLP) ML models that are used to predict Cataract status in the training and test sets and it was discovered that DT was the best model to predict the disease because it has minimum NIC value of 0.0288. This study demonstrates the appropriateness of NIC in identifying the best model for prediction of Cataract status and this would help healthcare professionals in making accurate informed decisions. Future study should compare the values of AIC, BIC and NIC and select the best model for prediction of Cataract status for more reliable prediction of the disease.

Keywords: Cataract, Training accuracy and loss, Network Information Criterion, Training and Test sets, Cross-validation.

1.0 INTRODUCTION

Eye is essential for navigating our environment but it suffered from diseases which are called eye diseases such as Cataract, Glaucoma, Refractive error, Diabetic retinopathy, Conjunctivitis. However, this study focused on Cataract because according to Adebayo *et al.* (2023), it was among the common eye diseases in the North-West of Nigeria.

Cataract is an eye condition in which the lens of the eye becomes cloudy. This causes vision to worsen, making it especially difficult to see things clearly. Some people vision only slightly affected, whereas others might lose their eyesight very quickly. It was estimated that the count of individuals living with vision impairment in the world to be over 2.2 billion. With respect to the aforementioned statistics of vision impaired people, Cataract was identified as the leading cause accounting for over thirty three percent (33%) and over forty five percent (45%) as the initial cause for blindness due to late detection and improper treatment (Nur *et al.*, 2021, Zheng *et al.*, 2020 and World Health Organisation, 2023). Cataract accounted for approximately 43% of visual impairment cases in Nigeria and 7.2% of the population over 40 years had Cataract in one or both eyes (National Institute of Health, 2023).

Cataract became alarming in the North-West zone of Nigeria, because cases are being reported frequently and it get to the extent that even children less than 10 years of age are affected and some become blind due to late diagnosis (Santos *et al.*, 2023). The individual affected by blindness finds it difficult to have gainful employment and this leads to dependence on family members and the society. This eye disease is threat to well-being of people and it need urgent attention (Marouf *et al.*, 2023).

In recent years, ML has emerged as a promising tool for medical diagnosis, offering the potential to analyze complex patterns in medical data and support clinical decision making. Similarly, the application of ML in ophthalmology has gained significant attention due to its ability to process large datasets including imaging and clinical information. However, the performance of these ML models heavily relies on the choice of model and its associated hyperparameters (Ismail *et al.*, 2024). With numerous ML algorithms available, identifying the best for a specific task such as Cataract prediction becomes necessary.

NIC has been proposed as a model selection tool that could effectively balance model fit and complexity. Unlike traditional model selection methods such as Akaike Information Criterion (AIC), Bayesian

Information Criterion (BIC) which was primarily designed for linear models, NIC was well-suited for complex network models including deep learning architectures commonly used in medical image analysis (Feng *et al.*, 2024).

Existing studies such as Marouf *et al.* (2023) formulated SVM model for prediction of Cataract and used cross-validation to select the best model. Schlosser *et al.* (2024) trained two ML models (SVM and DT) for prediction of Cataract and model with higher accuracy, sensitivity and specificity was considered as the best model. Maureen *et al.* (2023) used ML models for prediction of Cataract and model with higher accuracy, sensitivity and specificity in the cross-validation set was the best model. Roy *et al.* (2023) used measurement performance indices to determine the best model for prediction of eye diseases and Omkar *et al.* (2022) stated that model with higher accuracy in the cross-validation set was the best model. Moreover, Ismail *et al.* (2024) compared the performance of different ML models such as SVM, RF, XGBoost using AIC as the model selection criterion. The results showed that XGBoost had the lowest AIC value and was the best model to detect Cataract. Similarly, Feng *et al.* (2024) applied BIC for model selection and discovered that Neural Network (NN) has the smallest BIC value and was considered the best model for prediction of Cataract. While several studies have explored the use of ML for Cataract prediction, most of them relied on the use of Cross-validation, AIC, BIC to select best model and the use of NIC was not given much emphasis which is the gap identified and addressed in this study.

2.0 MATERIALS AND METHODS

2.1 Instrument for Data Collection

This study used personal interview method as instrument to collect data on DRFs, CRFs and LRFs of Cataract at NEC Kaduna after ethical approval was given on 21st October, 2024. The population of the study consist of patients from the North-West zone that visited Cataract Department with eye problem for medication from 25th Nov. to 19th Dec, 2024 daily observations. The sample size consists of 200 patients and covered patients within the ages of 10-80 years. To ensure representativeness of the sample, the study interviewed 35 patients each from Kano and Kaduna states, 26 patients each from Katsina, Jigawa, Sokoto, Zamfara and Kebbi states which make up total sample size of 200 patients. The dataset holds thirteen (13) risk factors, twelve (12) nominal and one (1) numerical. Cataract dataset had two Demographic Risk Factors (DRFs) age and sex; four Clinical Risk Factors (CRFs) Presence of Diabetes (POD), Higher Body Mass Index (HBMI), Previous Eye Injury (PEI) and Family History of Cataract (FHC); seven Lifestyle Risk Factors

(LRFs) Too Much Sun Exposure (TMSE), Frequent Expose to Radiation (FER), Too Much Coffee Consumption (TMCC), Frequent Use of Social Devices (FUSD), Smoking Cigarette (SMC), Medication with Steroid (MWS) and Too Much Alcohol (TMA) respectively as presented in Table 1.

Table 1: Description of Cataract Risk Factors

Cataract Risk Factors	Risk Name of Risk Factors	Type of Risk Factors
Age	Demographic	Numerical
Sex	Demographic	Nominal
Family history of Cataract	Clinical	Nominal
High body mass index	Clinical	Nominal
Presence of diabetes	Clinical	Nominal
Previous eye injury	Clinical	Nominal
Too much sun exposure	Lifestyle	Nominal
Frequent exposure to radiation	Lifestyle	Nominal
Frequent use of social devices	Lifestyle	Nominal
Too much coffee consumption	Lifestyle	Nominal
Smoking cigarette	Lifestyle	Nominal
Medication with steroid	Lifestyle	Nominal
Too much alcohol	Lifestyle	Nominal

2.2 Validity and Reliability of the Instrument

The instrument used in this study was checked for validity (i.e., accuracy) using face and construct validity methods. In face validity, the instrument was given to two (2) ophthalmologists at NEC Kaduna for scrutiny to ensure they measure what they supposed to measure. After necessary scrutiny, they are found to be valid both in the face of the ophthalmologists and in contact with patients.

In construct validity, the study took 5% of the sampled patients and then used Pearson's correlation coefficient formula to compute the value of r.

$$r = \frac{n \sum xy - \sum x \sum y}{\sqrt{[n \sum x^2 - (\sum x)^2][n \sum y^2 - (\sum y)^2]}} \quad (1)$$

The r value was 0.83 with P-value of 0.000 < 0.05, the instrument strongly valid.

To check reliability of the instrument, the study used Cronbach's alpha method which measure the internal

consistency of the questions in the instrument. Cronbach's alpha coefficient is given by

$$\alpha = \left[\frac{n}{n-1} \right] \left[1 - \frac{\sum_{i=1}^n \sigma_i^2}{\sigma_x^2} \right] \quad (2)$$

$\alpha = 0.873$, the result indicated a very higher level of consistency between the questions in the instrument.

2.3 Data Preprocessing and Preparation

Data preprocessing and preparation performed in this study was divided into two categories namely data cleaning and data balancing. Data cleaning steps were outlier detection and removal, missing value handling and data normalization.

For outlier detection, numerical variables are analysed using the interquartile range and according to this method, outlier was detected in numerical variables. No missing value because the patients interviewed gave complete and detailed information. To handle outliers removal, the study used the method applied by Khan *et al.* (2021) called One-sided Winsorization technique by replacing only the upper values with a specified percentile (95th percentile). Winsorization steps used were:

- i. Identify the instances/features that are farthest away from the median or mean
- ii. Apply Winsorization to the identified outliers. That is, choose a percentile (95th percentile) to replace the upper or lower extreme values. This percentile was called the Winsorization threshold
- iii. Analyze the results to ensure that the outliers have been effectively handled. Calculate the value below which 95% of the data falls.

Data normalization was performed because Cataract dataset have risk factors that differ in range and unit, this would reduce the models performance and accuracy. Secondly, prevent risk factors with larger scales from dominating the learning process. There are different types of data normalization, but this study used min-max scaling to transforms risk factors of the dataset to a specified range, usually between zero (0) and one (1). Other reasons for using the method are (i) the dataset was non-Gaussian and (ii) maintain the interpretability of the original values within the specified range. The min-max scaling is given by;

$$X_{normalized} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (3)$$

where X is a random risk factor value that is to be normalized, X_{min} is the minimum risk factor value in the dataset and X_{max} is the maximum risk factor value.

When X is minimum value, the numerator is zero ($X_{min} - X_{min}$) and hence, the normalized value is 0. When X is maximum value, the numerator is equal to the denominator ($X_{max} - X_{min}$) and the normalized value is 1 (Margaret, 2023).

For data balancing, the dataset was imbalance because the distribution of dataset between the classes not equal. That is, 135(67.5%) of the considered patients belong to Cataract (majority class) while 65(32.5%) belong to non-Cataract (minority class). To address this problem, the study used the method employed in the work of Kim *et al.* (2023) called Synthetic Minority Over-sampling Technique (SMOTE) and the steps applied are as follows:

- i. Check for class imbalance, that is, verify the datasets are imbalanced by checking the class distribution and calculate ratio (majority class size or minority class size)
- ii. Split the datasets into training and testing sets and apply SMOTE only to the training set to avoid overfitting
- iii. Use SMOTE library (imbalanced-learn in Python) to generate synthetic samples for the minority class.
- iv. Train SVM, DT, K-NN, NB and MLP on the oversampled training set and evaluate the models performance on the testing set
- v. Use metrics like precision, recall, F1-score and AUROC curve to evaluate the models performance.

2.4 Pearson Correlation Rank Based Feature Selection Method

This study used feature selection method called Pearson correlation rank based to select the Significant Risk Factors (SRFs) for prediction of Cataract, because the method focused on identifying the most important risk factors that are essential in training ML models for accurate prediction (Bustamante-Arias *et al.*, 2021).

Pearson correlation ($\rho_{X,Y}$) is given by

$$\rho_{X,Y} = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y} \quad (4)$$

where $\text{COV}(X, Y)$ is the covariance between X and Y and σ is the standard deviations (SDs) on X and Y. $\rho_{X,Y}$ value lies between -1 and +1, where -1 means a negative correlation between X and Y, 0 indicates no correlation between X and Y and +1 shows a positive correlation between X and Y. The closer the $\rho_{X,Y}$ value is to 1, the higher the correlation between X and Y. For selection of SRFs, Vidhya (2024) decision was implemented, that is, risk factors with P-value less than 0.05 ($P < 0.05$) were chosen as SRFs and those with P-value greater than 0.05 ($P > 0.05$) are not significant.

2.5 Evaluation of the Models Performance

ML Models (SVM, DT, K-NN, NB and MLP) used for prediction of Cataract status are evaluated in terms of their accuracy, sensitivity/recall, specificity, precision, F1- score and ROC curve using Equation (5) to (10). Accuracy measures the proportion of cases (eye-disease and non-eye disease patients) correctly classified, sensitivity/recall measures the fraction of positive cases (eye disease patients) that are classified as positive, specificity measures the fraction of negative cases (non-eye disease patients) that are classified as negative, precision measures the ability of the models not to classify a negative case as positive, F1- score is the harmonic mean of precision and recall and ROC curve measure the performance of the models in discriminating between eye disease and non- eye disease patients (Nathan, 2022).

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \quad (5)$$

$$\text{Sensitivity / Recall} = \frac{TP}{TP + FN} \quad (6)$$

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (7)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (8)$$

$$\text{F1- score} = 2 \frac{(\text{precision} \times \text{recall})}{(\text{precision} + \text{recall})} \quad (9)$$

$$\text{AUROC} = \int_0^1 \text{TPR}(FPR) dFPR \quad (10)$$

$$\text{TPR} = \text{Sensitivity / Recall}$$

$$\text{FPR} = 1 - \text{Specificity} = \frac{FP}{FP + TN}$$

where TP, TN, FP, FN, TPR and FPR denotes True Positive, True Negative, False Positive, False Negative, True Positive Rate and False Positive Rate respectively.

2.6 Cross -Validation of the Models

This study employed cross-validation to validate the performance of the models used for prediction of Cataract status. There are several types of cross-validation techniques such as k-fold cross-validation, leave-one-out cross-validation, holdout cross-validation, stratified cross-validation but this study used k-fold cross-validation because it maximizes the use of limited data, provides a more robust and reliable performance estimate and minimizes the risk of overfitting to a particular data split (Erickson & Kitamura, 2021).

To use k-fold cross-validation when $k = 5$, Cataract sampled data was randomly partitioned into five equal sized sub-sample. One sub-sample was used for testing and the remaining four (4) sub-samples for training. The procedure runs five times and mean metrics across folds was gotten.

2.7 Network Information Criterion

NIC was used to determine the best model for prediction of Cataract status. To achieve this, NIC values of the five ML models were computed and model with minimum NIC value was considered the appropriate model to predict the eye disease. NIC is given by

$$\text{NIC} = -\frac{1}{T} \ln L(\hat{w}) + \frac{\text{tr}(BA^{-1})}{T} \quad (11)$$

where A and B are matrices and defined to be

$$A = -E[\nabla^2 L_t], \quad B = E[\nabla L_t \nabla L_t^T], \quad \ln L(\hat{w}) \text{ is}$$

the estimated maximum log likelihood, T is the number of observations, ∇ denote the gradient and tr is the trace of BA^{-1} (Morata *et al.*, 1994).

3. 0 RESULTS AND DISCUSSIONS

3.1 Identification of Significant Risk Factors of Cataract

Pearson correlation ranked-based feature selection method results in Table 2 revealed that out of thirteen (13) risk factors of Cataract, twelve (12) were significant ($P < 0.05$) and one (1) not significant ($P > 0.05$). The SRFs were two (2) DRFs age and sex, four (4) CRFs namely FHC, HBMI, POD and PEI and six (6) LRFs

namely TMSE, FER, FUSD, TMCC, MWS and SMC while TMA was the non-SRF. The twelve significant risk factors have positive correlation. That is, as the risk factor increases, the risk of having Cataract also increases and vice-versa. A negative correlation exists between TMA and output. That is, as one increases the other one decreases and vice-versa.

Table 2: Significant Risk Factors of Cataract

Risk Factors	Correlation Values	P-Value
Age	0.2432	5.2136e-04
Sex	0.2179	1.9307e-03
Family history of Cataract	0.5866	7.0416e-20
High body mass index	0.7059	1.7678e-31
Presence of diabetes	0.6805	1.4928e-28
Previous eye injury	0.6417	1.3401e-24
Too much sun exposure	0.6836	6.8481e-29

Frequent exposure to radiation	0.6537	9.2429e-26
Frequent use of social devices	0.5599	6.7350e-18
Too much coffee consumption	0.5970	1.0595e-20
Smoking cigarette	0.2816	5.3418e-05
Medication with Steroid	0.2087	3.0209e-03
Too much alcohol	-0.0256	7.1845e-01

3.2 Prediction of Cataract Status

Before prediction of Cataract status (Cataract and Non-Cataract patients), the study performed data split. The dataset was splitted into training and test subsets for model training and evaluation. The training set contained 80% (160) of the data which was used for training the model and the remaining 20% (40) was held out as the testing set to assess the model performance. The results of splitting Cataract dataset was presented in Table 3.

Table 3: Splitting of Cataract Dataset into Training and Test Subsets

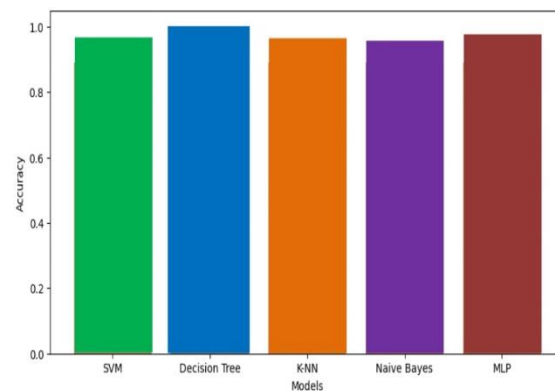
	TRAINING SET			TEST SET		
	CATARACT STATUS	Non-Cataract	STATUS Total	CATARACT	Non-Cataract	STATUS Total
Count	105	55	160	30	10	40
Percentage	65.6	34.4	100.0	75	25	100.0

After splitting the dataset, the five (5) ML models are trained using the SRFs. To achieve this, the study used supervised learning algorithms and L1 Regularization Technique to prevent overfitting and improve generalization using Scikit – learn in Python. Instance of the models were created and the models are trained using `model.fit(x_train, y_train)`.

Hyperparameter tuning was carried out before training using Grid search because this search defines set of parameters values to search over and the algorithms tries all possible combination.

The models initially used their default settings so that as each model was adjusted to the data in the training process, the hyperparameters were also adjusted and at the end of the training, the hyperparameter values of the models were computed.

After estimating the hyperparameter values of the models, training accuracy and training loss were also gotten as presented in Figure 1.



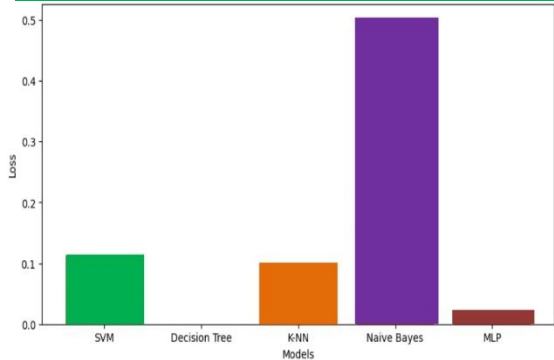


Figure 1: Training Accuracy and Loss of the Models

The models achieved 0.97, 1.00, 0.96, 0.96, and 1.00 training accuracy; 0.1118, 0.000, 0.0993, 0.5013 and 0.0118 training loss and according to Lenz *et al.* (2018) interpretation; SVM, DT, K-NN, NB and MLP have

perfect training accuracy. DT, K-NN and MLP perfect training loss, SVM good training loss and NB poor training loss.

The trained models are used to predict Cataract status in the training and test sets. The results presented in Table 4 showed that the SVM model predicted 96.2% and 90.8% Cataract patients, 94.5% and 80.0% Non-Cataract patients in the training and test sets. DT model predicted 98.1% and 96.7% Cataract patients, 98.2% and 90% Non-Cataract patients in the training and test sets. K-NN model predicted 97.1% and 93.3% Cataract patients, 94.5% and 80% Non-Cataract patients in the training and test sets. NB model predicted 95.2% and 86.7% Cataract patients in the training and test sets, 92.7% and 70% Non-Cataract patients in the training and test sets. MLP model predicted 98.1% and 93.3% Cataract patients, 94.5% and 90% Non-Cataract patients in the training and test sets

Table 4: Prediction of Cataract Status

Model	Observed	Classification of Eye Status				
		Cataract	Non-Cataract	Total	Percentage of Predicted Patients	
SVM	Training set	Cataract	101	4	105	96.2
		Non-Cataract	3	52	55	94.5
		Total	104	56	160	
	Test set	Cataract	27	3	30	90.8
		Non-Cataract	2	8	10	80.0
		Total	29	11	40	
DT	Training set	Cataract	103	2	105	98.1
		Non-Cataract	1	54	55	98.2
		Total	104	56	160	
	Test set	Cataract	29	1	30	96.7
		Non-Cataract	1	9	10	90.0
		Total	30	10	40	
K-NN	Training set	Cataract	102	3	105	97.1
		Non-Cataract	3	52	55	94.5
		Total	105	55	160	94.5
	Test set	Cataract	28	2	30	93.3
		Non-Cataract	2	8	10	80.0
		Total	30	10	40	
NB	Training set	Cataract	100	5	105	95.2
		Non-Cataract	4	51	55	92.7
		Total	104	56	160	
	Test set	Cataract	26	4	30	86.7
		Non-Cataract	3	7	10	70.0
		Total	29	11	40	
MLP	Training set	Cataract	103	2	105	98.1
		Non-Cataract	3	52	55	94.5
		Total	106	54	160	
	Test set	Cataract	28	2	30	93.3
		Non-Cataract	1	9	10	90.0
		Total	29	11	40	

3.3 Evaluation of the Models Performance for Prediction of Cataract

Evaluation of the models performance presented in Table 5 showed that SVM model achieved 98.5% accuracy, 94.8% sensitivity, 92.3% specificity, 96.2% precision, 95.5% F1-score and 1.00 AUROC. DT model had 99.5% accuracy,

97.8% sensitivity, 96.9% specificity, 98.5% precision, 98.1% F1-score and 1.00 AUROC. The accuracy, sensitivity, specificity, precision, F1-score and AUROC of K-NN model were 97.8%, 96.3%, 92.3%, 96.3%, 96.3% and 1.00. NB model had 96.3% accuracy, 93.3% sensitivity, 89.2% specificity, 94.7% precision, 94.0% F1-score and 1.00 AUROC. MLP model achieved 99.2% accuracy, 97.0% sensitivity, 93.8% specificity, 97.0% precision, 97.0% F1-score and 1.00 AUROC respectively.

Table 5: Evaluation of the Models Performance for Prediction of Cataract

Model	Measurement Performance Indices					
	Accuracy (%)	Sensitivity/Recall (%)	Specificity (%)	Precision (%)	F1-Score (%)	AUROC
SVM	98.5	94.8	92.3	96.2	95.5	1.00
DT	99.5	97.8	96.9	98.5	98.1	1.00
K-NN	97.8	96.3	92.3	96.3	96.3	1.00
NB	96.3	96.3	89.2	94.7	95.5	1.00
MLP	99.2	97.0	93.8	97.0	97.0	1.00

3.5 5-Folds Cross-Validation of the Models Performance

The 5-folds cross-validation result presented in Table 6 showed that the mean metrics across folds are as follows: SVM had 98.4% accuracy, 94.6% sensitivity/recall, 92.1% specificity, 96.2% precision, 95.4% F1-score and 1.00 AUROC curve.

Table 6: 5-Folds Cross-Validation of the Models Performance

Model	Measurement Performance Indices					
	Accuracy (%)	Sensitivity/Recall (%)	Specificity (%)	Precision (%)	F1-Score (%)	AUROC Curve
SVM	98.4	94.6	92.1	96.2	95.4	1.00
DT	99.4	97.7	96.8	98.4	98.0	1.00
K-NN	97.6	96.2	92.1	96.3	96.2	1.00
NB	96.2	96.2	89.1	94.6	95.4	1.00
MLP	99.1	96.8	93.6	96.9	96.8	1.00

DT achieved 99.4% accuracy, 97.7% sensitivity/recall, 96.8% specificity, 98.4% precision, 98.0% F1-score and 1.00 AUROC curve. K-NN had 97.6% accuracy, 96.2% sensitivity/recall, 92.1% specificity, 96.3% precision, 96.2% F1-score and 1.00 AUROC curve. NB achieved 96.2% accuracy, 96.2% sensitivity/recall, 89.1% specificity, 94.6% precision, 95.4% F1-score and 1.00 AUROC curve. MLP had 99.1% accuracy, 96.8% sensitivity/recall, 93.6% specificity, 96.9% precision, 96.8% F1-score and 1.00 AUROC curve respectively.

3.4 Result of Model Selection using NIC

The NIC values of the models were 0.0854, 0.0288, 0.0950, 0.5113 and 0.0305 respectively. From Table 7, it could be seen that DT had the lowest NIC value of 0.0288 and was considered the best model to predict Cataract status.

Table 7: NIC Value of the Models

NIC Value of the Models

Dataset	SVM	DT	K-NN	NB	MLP
Cataract	0.0854	0.0288	0.0950	0.5113	0.0305

4.0 CONCLUSION

This study aimed at identifying best model for prediction of Cataract status using NIC. It was found that out of the thirteen risk factors of Cataract, twelve were significant ($P < 0.05$) and one not significant ($P > 0.05$). Five ML models are trained using the SRFs for prediction of Cataract status, evaluated using measurement performance indices and cross-validated using 5-folds cross-validation. All the models performed well with perfect accuracy, sensitivity, specificity, precision, F1-score; excellent AUROC and perfect 5-folds cross-validation. The NIC result showed that among the five models, DT was the best model to predict the eye disease because it had the lowest NIC value of 0.0288 when compared with SVM, K-NN, NB and MLP with NIC values of 0.0854, 0.0950, 0.5113 and 0.0305 respectively. This study demonstrates the appropriateness of NIC in identifying the best model for prediction of Cataract status and this would help healthcare professionals for making accurate informed decisions. Future study should compare the values of AIC, BIC and NIC and select the best model for prediction of Cataract status for more reliable prediction of the disease.

LIMITATION OF THE STUDY

Small sample size $n = 200$ is the limitation of the study. There is need to check the performance metrics using larger and independent datasets, this would justify the performance of the models using limited sample size ($n = 200$). Also, there is need to cross-validate the models using larger, independent datasets.

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